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An Efficient Data Analytics and Optimized Algorithm for Enhancing the Performance of Image Segmentation Using Deep Learning Model

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Abstract: Image segmentation is the key topic in computer vision and image processing with applications like robotic perception, scene understanding, video surveillance, image compression, medical image analysis, and augmented reality among many others. There are numerous algorithms are developed in the literature for image segmentation. This paper provides a broad spectrum of pioneering works for instance and semantic level segmentation with mask Region based Convolution Neural Network with Monarch butterfly Optimization (RCNN-MBO) architecture. The system is initially constructed in a Python environment with images of people and animals being input. Remove the unnecessary data from the gathered datasets during the pre-processing stage. Next, use a stochastic threshold function to segment the image. Then update the segmented images into a designed model for detecting and classifying a group of images. The main goal of the designed approach is to attain accurate prediction results also improve the performance of the designed model by attaining better results. To enhance the performance, two activation functions were used and MBO fitness is updated in the classification layer. It improves the prediction results and takes less time to detect and classify images. Finally, the experimental outcomes show the reliability of the designed approach by other conventional techniques in terms of accuracy, precision, sensitivity, specificity, F-measure, error rate, and computation time.
Keywords: Segmentation, Softmax Activation Function, Relu Activation Function, Region based Convolutional Neural Network, Monarch Butterfly Optimization.

I. INTRODUCTION

A significant quantity of information has recently been gathered about the movements and behaviors of wild animals using information from both space and time. Many innovative tools have been employed to locate wild animals and record their movements [1]. The quick expansion of wildlife research data has made it possible to more effectively identify target feral creatures and their behavior [2]. A fraction of the negative repercussions of human-animal conflict includes injury to human life and destruction of human crops and equipment [3]. The sort of behavior of wild animals is determined by the study of ethology, which also transmits the animal during image processing [4]. To costly data and display lengthy towards a shade for using DL system, monitoring cameras must be massive. It starts "state of the art" for DL that is used for distinguishing between different kinds of wild animals and their behaviors using image data [5]. The longitudinal dataset potential duration for organic issues can be attained by the image dataset [6]. Employing artificial intelligence to process a sizable image dataset can help find, monitor, and identify specific wild animals [7]. With the help of image categorization, which makes it possible to remove the environment from a picture, an immediately applicable of animals can be made using annotated data [8]. The accessible model of week machine learning to the images has been generated using the DL approaches, which were for analysing and image speed up analysis approach [9]. Certain established techniques have been created to limit the use of image analysis methods from wild animals, such as the fragmentation approach and distance method, chemical or physiological method, or manual inspection identification approach [10]. Whereas the image component increases in size and the aesthetic feature change the image classification across several frames, there are still substantial hurdles [11]. The multi-layered scene classification algorithm incorporates the picture into elevated amounts of characteristics to find wild animals [12]. The first stage in image classification is to display the image structure that was obtained during image collection. Most current research is being done on dynamical object detection using computer

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vision (CV), which uses visual monitoring to identify scenes with wild animals [13].

The DL approach employs several techniques is used for recognizing, categorize animal's appearance from the image recording [14]. As a result, the naked eye may also foretell animal appearance in the main image. Therefore, humans are severely restricted in their capacity to capture animal images [15]. The many methods and implementation techniques that use the alarm system for humans and safeguard them from wild animals have increased our knowledge of ethology to a higher level. To locate and recognize animals inside the woods or on highways, new technologies like sensors, radiofrequency, and GPS systems are being developed [16, 17]. To recover and recognize the actual image of animals from the image classification process, the deep learning approach uses a variety of methods. Recurrent neural networks Media Software and Applications and similarity approaches used for classification tasks are the two most well-known deep learning paradigms [18]. Deep learning's fundamental captured image categorization method has two requirements for faster performance, as well as tensor processing units (TPUs) and graphics processing units (GPUs). Whereas the neural computes stick (NCS) characteristic, which enables the CNN running is good profile and forms ranging in classification task [19], it is also employed for optimizing low operating system power. The information is automatically extracted from the visual input using computer vision's deep learning technique. The scene classification method is utilized to identify particular animal species and their look [20]. The primary goal of the designed model is for segmenting the input images and identifies the borders using the stochastic threshold function. Also, design an RCNN model with ReLU and Softmax function to improve the classification performance. Additionally, MBO is used to improve the prediction results and attained better experimental outcomes.

II. Related Work

Between the various examination works on a group of images identification, few of the research works are reviewed here,

In 2022, Vatsavayi, V.K., et.al, [21] presented a wild animal’s classification and identification as of image arrangements by means of a hybrid deep residual convolutional neural network (DRCNN). Firstly, the datasets are collected, and then image sequences are converted to image frames. Secondly, the image frames are given to the Fast Average Peer Group Filter (FAPGF) method for eliminating noise. Thirdly, the pre-processed image frames are given to the segmentation method for subtracting the background portion. Fourthly, the segmented image frames are fed towards the process of feature extraction to extract texture, size, and colour features. At last, the extracted features are fed towards the hybrid DRCNN for the classification process. Moreover, Transient Search optimization Algorithm (TSOA) is for updating wild animal’s place and position. It provides higher accuracy with lower precision.

In 2021, Chandrakar, R., et.al, [22] have presented a utilizing Deep CNN (D-CNN) and genetic segmentation, a technique for automatic animal identification and detection. In this, a CNN ability to categorize the input animal images is displayed. For segmentation, a Genetic Algorithm (GA) is used, and for classification, a three-layer neural network is employed. The 100 unique subjects, ten images and two classes are taken in the datasets in each class is constructed for training and analyzing the suggested work. It provides a higher f-measure with lower sensitivity. In 2022, Chithra, P.L., et.al, [23] presented image identification CAPTCHA against meddlers using a convolutional neural network. The CAPTCHA was developed for meddler images, and it was later tested to see if the images were strong or recognizable. Additionally, the modified face convolutional neural network with Xtreme gradient boosting (XGB-MANFA) was suggested due to the imbalanced dataset issue. It provides a lower error rate with higher sensitivity.

In 2022, Ricolfe-Viala, C, et.al, [24] presented an Image-Labelling Technique Robot Perception Skills are Improved. In this study, a quick, almost entirely automated technique for labelling images is proposed and put to the test using a robot perception challenge. Rectangles or masks are used to rapidly and precisely classify photos of items taken against particular backdrops. To enhance the image set's training potential, identified objects can be synthesized with various backgrounds in a subsequent stage. This kind of labelling creates a database that convolutional networks may use to easily detect hand fingers with little labelling labour. This suggested approach speeds up the convolutional neural network model's training process and significantly improves the labelling process. It provides lower computation time with a higher f-measure. In 2022, Hussain, A., et.al, [25] presented a DL-Based Activity Identification for the Safety of Pets Using Wearable Sensors. CNN 1D is discussed in this study for signal manufacturing systems such as sensor-based health monitoring systems, patient-individual ECG categorization, and anomaly identification in industrial settings. To create a cutting-edge system is the main objective of this method and it identifies and categorizes activities using data from accelerometers and sensors of

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gyroscope. The presented 1D CNN is used for monitoring wild animal's activities. The 1D CNN methods will be useful for tracking canine behavior and real-time activity monitoring. It provides higher specificity with lower accuracy.

The main common issues of existing segmentation models are less segmentation accuracy and low-performance recall and precision. Additionally, more execution time is taken for detecting the group of images. Moreover, the computational cost is high and the data complexity issues are obtained because of the vast amount of data. To overcome these issues designed an RCNN-based optimization model for improving the segmentation results of a group of images.

III. PROPOSED METHODOLOGY

Nowadays, segmentation is the most important research domain and also provides essential information. To enhance the segmentation accuracy and efficiency the investigators have proposed deep learning with a metaheuristic algorithm. This algorithm can provide better outcomes and effectively solve the different image issues. Therefore, in this paper; input images are collected and updated to the preprocessing. In the pre-processing stage, remove the redundant information from the collected datasets. Then segment the image using the stochastic threshold function for accurate segmentation. Then design a novel Region based Convolution Neural Network with Monarch butterfly Optimization (RCNN-MBO) framework. During testing, two types of activation functions are used such as ReLU and softmax activation function. After that, that updates Monarch Butterfly Optimization (MBO) [26] in the softmax activation layer for accurate detection. Finally, the simulation outcomes demonstrate the advantage of using RCNN-MBO for image segmentation in terms of classification accuracy.

3.1 Dataset collection

Generally, a group of images is collected from the net source, and the input images such as cats, dogs, and humans are tested and trained in the system. Moreover, 70% of the dataset are utilized for training phase and 30% of datasets are utilized for the training phase. During training, 5153 cat images, 4739 dog images, and 6719 human images were taken. For the testing process 500 cat images, 500 dog images, and 500 human images were taken. Initially, the datasets were preprocessed for removing the noise and redundant information from the dataset. Moreover, resizing the pixel size into $227 \times 277 \times 1$ and a matrix type in a numpy array also improves the image quality and enhances the segmentation results.

3.2 Preprocessing

Generally, preprocessing phase is utilized for removing the redundant information from the collected datasets. Also, normalizing the dataset features is helpful to standardize the dataset and improve its quality of the dataset. The process of data normalization is obtained using Eqn. (1),

$$p_n = \frac{W - \eta}{\varphi} \tag{1}$$

Where, W is denoted as the dataset features, η is represented as the mean value of every dataset feature, and φ is considered as the corresponding standard deviation.

3.3 Segmentation

Originally, threshold-based segmentation is the simplest technique for segmenting the images from the dataset. It can subtract the background noise from the images. Here, segmentation is processed using Stochastic Threshold Function (STF) [27]. Furthermore, segmentation allocates and separates each pixel from the pre-processed images. Thus the designed model separates the images into minor segments with the help of colour features. Additionally, the STF is applied to each pixel and the single threshold value is considered as T_1^*. Moreover, the STF objective function is helpful for identifying the value of T_1^* that is obtained using Eqn. (2).

$$K(a,b) = \begin{Bmatrix} 0, & f(a,b) < T_1^* \\ 1, & f(a,b) < T_1^* \end{Bmatrix} \tag{2}$$

Let, T_1^* is expressed as Eqn. (3)

$$T_1^* = T_1^*\left[a, b, h(a,b), f(a,b)\right] \tag{3}$$

Therefore, $f(a,b)$ is denoted as the grey level value, and the objective point of $f(a,b) > T_1^*$ is known as the background point. Moreover, $h(a,b)$ is represented as local property. Moreover, segmented images are shown in fig.2.

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Fig.2 Segmented images using optimization algorithm.

Thus the segmentation of images assessed the background from the input images and routinely deducts the background via applying the threshold.

3.4 Process of RCNN-MBO

After the segmentation process, update the segmented images into the designed RCNN-MBO model for accurate detection and classification. Moreover, the segmented images are updated to the designed model input layer. The classification of the images of humans and animals makes use of a convolution neural network. Compared to previous methods, our neural network delivers results more quickly and effectively. There are input, output, and hidden layers in every RCNN. The invisible layer contains several function layers. Convolutional, polling, fully connected, and normalized layers make up the majority of functional layers. Thus the designed model applied two activation functions as Relu activation function and the softmax activation function. Moreover, the activation function of Relu is processed in the convolution layer for feature extraction. It is one of the non-linear activation functions and is accomplished on multi-layer networks. It filters the information and forwards it through the network. Also, the activation function of softmax is employed in the fully connected layer which helps the output layer of the network and predicts the multinomial probability. Furthermore, the activation function of softmax is utilized for the multi-class classification problems.

3.4.1 Convolutional layer

The main part of the developed RCNN model is the convolutional layer and contains filter that improve the input quantity. During the convolution process, each filter calculates the input quantity with dot operation. The convolutional layer does not perform a manual operation to extract the image attributes. It can be calculated as

$$f(h(t)) \underline{\underline{def}} \int_{-\alpha}^{\alpha} f(\Gamma) h(t-\Gamma) d\Gamma \qquad (4)$$

From the Eqn. (4), convolution is the multiplication of reversed and shifted functions.

3.4.2 ReLU Function

It is a non-saturated function it removes all the negative points. Moreover, feature extraction is processed in this stage, which extracts the texture features from the collected dataset and the threshold is zero, it is expressed as Eqn. (5). Also the process of feature extraction is obtained using Eqn. (6).

$$f(y) = \max(0, y) \qquad (5)$$

$$F_e(t) = p_n(W - t_x) \qquad (6)$$

Where, p_n is denoted as the pre-processed input data, W is represented as total features and t_x is considered as the extracted texture features. The RCNN framework considers the spatial and temporal information present in the image, thereby learning the structural features of the images effectively. This results in higher classification accuracy.

3.4.3 Pooling layers

Moreover, global and local pooling decreases the image measurements using the combination of particular neuron and output neuron. Moreover, pooling layer computes the average value neurons and maximum value neurons. Hereafter, the average and maximum pooling can be calculated as Eqn. (7).

$$f_{MP1}(Y) = \max_{j,i}(j,i)$$
$$f_{AP1}(Y) = \frac{1}{m+n} \sum_{j=1}^{m} \sum_{i=1}^{m} Y(j,i) \qquad (7)$$

Eqn. (6), $f_{MP1}(Y)$ is denoted as the maximum pooling that proceeds the every maximum value and $f_{AP1}(Y)$ is considered as the average pooling that proceeds the every average value.

3.4.4 Fully linked layers

It is also known as a thick layer. It is situated at the last part of RCNN. Neurons present in this linked layer are fully linked to all activation layers in the earlier stage. The thick layer is linked between the single layers of every neuron to another layer.

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IV. Results and Discussion

Here, a novel intelligent segmentation method using an optimization-based convolution neural framework is analyzed and the proposed scheme is executed in python tool. The performance metrics of the proposed RCNN-MBO method such as specificity, f-measure, sensitivity, precision, error rate, computation time, and accuracy. The efficacy of the proposed RCNN-MBO technique is likened to the existing techniques, like a DRCNN-TSOA [21], (D-CNN-GA) [22], (XGB-MANFA) [23] respectively. The confusion matrix of the designed model is shown in fig.3.

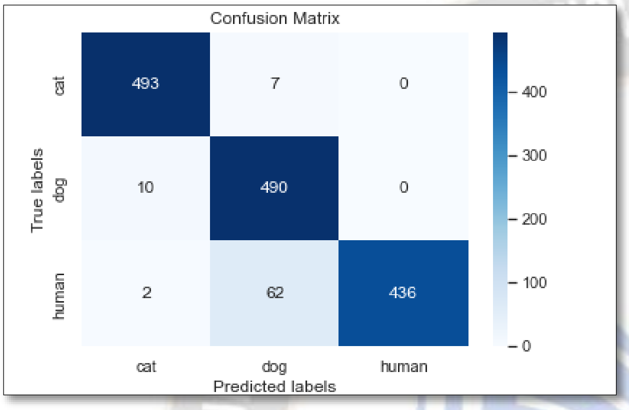

Fig.3 Confusion matrix for training and testing data

4.1 Simulation results

Figures 5-11 and Tables 1-7 shows the simulation results of a novel intelligent segmentation method using an optimization-based convolution neural framework.

Table 1: Accuracy Analysis

Methods	Accuracy	
	Human	Pet
DRCNN-TSOA	72	87
D-CNN-GA	75	78
XGB-MANFA	89	69
RCNN-MBO(Proposed)	98	97

Table.1 shows the accuracy performance. The proposed RCNN-MBO technique shows 34.89%, 29.09% and 56.94% higher accuracy for humans likened with the existing approaches like DRCNN-TSOA, D-CNN-GA, and XGB-MANFA respectively. Then the proposed RCNN-MBO technique shows 29.06%, 19.67%, and 39.56% higher accuracy for pets likened with the existing approaches like DRCNN-TSOA, D-CNN-GA, and XGB-MANFA respectively.

Table 2: Precision Analysis

Methods	Precision	
	Human	Pet
DRCNN-TSOA	67	87
D-CNN-GA	89	67
XGB-MANFA	76	70
RCNN-MBO(Proposed)	99	97

Table.2 shows the precision performance. The proposed RCNN-MBO technique shows 22.78%, 38.56% and 21.58% higher precision for humans likened with the existing approaches like DRCNN-TSOA, D-CNN-GA, and XGB-MANFA respectively. Then the proposed RCNN-MBO method displays 23.78%, 20.67%, and 33.78% higher precision for pets likened with the existing approaches such as DRCNN-TSOA, D-CNN-GA, and XGB-MANFA respectively.

Table 3: Sensitivity Analysis

Methods	Sensitivity	
	Human	Pet
DRCNN-TSOA	63	67
D-CNN-GA	78	89
XGB-MANFA	67	75
RCNN-MBO(Proposed)	97	99

Table.3 shows the sensitivity performance. The proposed RCNN-MBO technique shows 19.67%, 22.78% and 43.78% higher sensitivity for humans likened with the existing approaches such as DRCNN-TSOA, D-CNN-GA, and XGB-MANFA respectively. Then the proposed RCNN-MBO technique displays 22.78%, 14.67%, and 26.89% higher sensitivity for pets likened with the existing approaches like DRCNN-TSOA, D-CNN-GA, and XGB-MANFA respectively.

Table 4: Specificity Analysis

Methods	Specificity	
	Human	Pet
DRCNN-TSOA	64	87
D-CNN-GA	78	67
XGB-MANFA	87	74
RCNN-MBO(Proposed)	97	98

The specificity performance is displays in the table 4. The proposed RCNN-MBO technique shows 20.89%, 26.89% and 29.56% higher specificity for humans likened with the existing approaches like DRCNN-TSOA, D-CNN-GA, and XGB-MANFA respectively. Then the proposed RCNN-MBO technique shows 20.83%, 18.78%, and 25.87% higher specificity for pets likened with the existing approaches like DRCNN-TSOA, D-CNN-GA, and XGB-MANFA respectively.

Table 5: F-measure Analysis

Methods	F-measure	
	Human	Pet
DRCNN-TSOA	84	63
D-CNN-GA	60	78
XGB-MANFA	89	86
RCNN-MBO(Proposed)	97	99

The f-measure performance is displays in table 5. The proposed RCNN-MBO technique shows 22.78%, 33.98% and 28.09% higher f-measure for humans likened with the existing approaches like DRCNN-TSOA, D-CNN-GA, and XGB-MANFA respectively. Then the proposed RCNN-MBO technique shows 22.78%, 40.90% and 34.78% higher f-measures for pets likened with the existing approaches such as DRCNN-TSOA, D-CNN-GA, and XGB-MANFA respectively.

Table 6: Error rate analysis

Methods	Error Rate
DRCNN-TSOA	0.9
D-CNN-GA	0.7
XGB-MANFA	0.8
RCNN-MBO(Proposed)	0.2

Table.6 shows the error rate performance. The proposed RCNN-MBO technique shows 37.67%, 28.56%, and 45.67% lower error rates likened with the existing approaches such as DRCNN-TSOA, D-CNN-GA, and XGB-MANFA respectively.

V. Conclusion

This research paper designs a novel RCNN-MBO framework for improving the segmentation of a group of images. Moreover, two activation functions are processed in RCNN to improve the classification performance of RCNN. Moreover, the developed model is implemented in the python tool and the input images are collected from the net source and trained in the system. The input images contain the human, dog, and cat image datasets that are pre-processed for removing redundant information and the images are segmented using STF. Thus the designed model shows better performance using two activation layers and the classification layer update MBO fitness for improving the detection and classification results. The experimental outcomes show better results and the results are validated with other prevailing models. Finally, the designed model attains 98% and 97% accuracy for predicting a group of images. Thus the designed model has the capability of detecting and classifying groups of images from input images.

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