



# An Efficient Medical Image Processing Approach Based on a Cognitive Marine Predators Algorithm

**Dr. Sunita Chaudhary**

Professor, Computer Science and Engineering,  
Marudhar Engineering College,  
Bikaner, Rajasthan,  
ORCID ID-0000-0001-8913-4897  
choudhary.sunita@marudhar.ac.in

## Abstract

Image processing aims to enhance the image's quality such that it is simple for both people and robots to understand. Medical image processing and Biomedical signal processing have many conceptual similarities. Medical image processing involves evaluation, enhancement, and presentation. The focus of medical imaging is on obtaining photographs for both therapeutic and diagnostic reasons. In the existing Marine Predator Algorithm, different disadvantages are experienced when various automated optimization algorithms are used to the problem of ECG categorization. The proposed method follows the flow outlined here: data collection, image preprocessing using histogram equalization, segmentation using the Otsu threshold algorithm, feature extraction using the contour method, feature selection using the Neighborhood Component Analysis (NCA) algorithm, and Cognitive Marine Predator Algorithm (CMPA) as the proposed method. By using the Cognitive Marine Predators Algorithm (CMPA), base layers are fused to use the greatest feasible parameters, producing enhanced high-quality output images. Finally, the image processing performance is analyzed. The proposed approaches overcome the drawbacks of existing algorithms and increase the quality of medical images efficiently.

**Keywords:** Medical image processing, Cognitive Marine Predator Algorithm (CMPA), Neighborhood Component Analysis (NCA), Imaging technologies

## I. INTRODUCTION

When it comes to protecting human health and monitoring illness, medical imaging and image interpretation are critical. Medical imaging equipment has seen a surge in use in recent years, thanks to advancements in technology. Medical imaging technology development is still undergoing intense scrutiny. In 2018, an estimated 18.1 million people will be diagnosed with cancer, and 9.6 people will die from the disease. To eradicate many deadly illnesses, early identification is essential. When compared to the global population, it is understandable that it is difficult to get an early diagnosis. Expertise is scarce in low-income nations. Medical photographs, in particular, need a lengthy examination because of their size and complexity [1]. Image processing methods like MRI have grown fast in recent decades, prompting the development of digital image processing algorithms specifically designed for these frequently enormous imaging datasets (3-dimensional and higher-dimensional). Quantitative information may be extracted from images using techniques including aberration reduction, identification, and separation by anatomical segmentation, and spatial image registration. The academic research community is primarily responsible for the

development of medical image analysis methods. As a result, open software platforms may facilitate the translation of innovative technological advances to the MRI hardware makers, doctors, and the biomedical sector [2]. Medical imaging may benefit from the fact that various datasets of the same patient, such as different MR sequences, PETCT scans, or innovative hybrid CT-MR imaging modalities, are often accessible. As a result, even if a scan was obtained using a different modality, leveraging redundant information from across the datasets may assist recover lower-quality or lower-resolution images. With this, the inherent difficulty of single-image restoration is alleviated: the illusion of data that is not there in the original picture. To make medical picture improvement easier to understand, we've integrated the technique with adaptive image filters. This separates the service's outputs from the image undergoing processed [3]. It is very challenging to analyze medical pictures for illness detection and diagnosis because of the growing complexity of the images. Furthermore, as can be seen from the provided image, the area is heavily diseased. Image processing approaches utilized for segmenting and categorizing tumor-infected areas are to be evaluated in this data analysis. Although medical images must be analyzed in



detail to obtain useful information. Hence, we proposed the CMPA for efficient image visualization in medical image processing.

**Contributions to the paper**

- The histogram equalization method is used to improve the contrast in the raw dataset.
- The Otsu threshold technique is used to convert an image into a collection of regions of pixels in the dataset.
- The contour method for feature extraction is used to detect and extract the boundaries in the dataset.
- The Neighborhood Component Analysis (NCA) algorithm is used to identify the relevant feature subsets.

The remainder of the paper is structured as follows: In part II, a literature survey is provided. Described in Part III is a proposed approach. Part IV includes a result and discussion. Part V is the conclusion section.

**II. LITERATURE SURVEY**

Study [4] provided a brief history of deep learning and its use in medicine in the recent decade. Furthermore, three examples of future research directions for COVID-19 medical image processing are provided from China, Korea, and Canada. Study [5] described the most advanced deep learning architecture and its optimization. Deep learning approaches in medical imaging and accessible data are covered as the session makes a decision. Various CNN structure and their medical imaging applications have been thoroughly discussed by the study [6]. There has also been a comparison of the high tech in medical imaging classification with different available techniques. The latest work including potential future directions is discussed in this study [7] for deep learning algorithms applied in clinical image analysis. Deep learning in the subject of medical image processing, is a valuable source of information. After that the difficulties in applying it to medical imaging and some unresolved research issues. Deep learning is used to develop an effective medical image processing system. Web-based image processing systems are subjected to a series of security checks by the creators. When it comes to evaluating security in medical image processing, study [8] recommends using FAHP and TOPSIS, two techniques that use fuzzy analysis and similarity to an ideal solution. Using Morphing, the study [9] offered a new method for recreating 3D point clouds from 2D images. Mimics are used to create a 3D surface model of soft tissue (live) from a sequence of 2D CT scans. Study [10] provided an overview of image

processing-based approaches for detecting cancers of the lung, brain, and liver. In an attempt to handle enormous datasets and offer reliable and efficient findings in the diagnosis of cancer, mechanized and computer-aided detection systems (CAD) with artificial intelligence are utilized as detection techniques.

**III. PROPOSED APPROACHES**

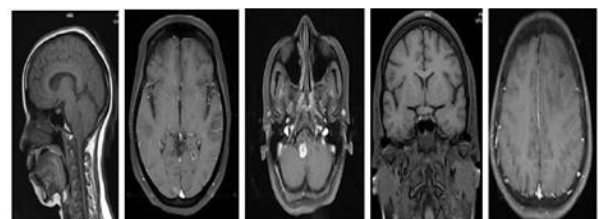
In this paper, we proposed the CMPA for medical image processing. Medical image processing includes the use and investigation of 3D datasets of the human internal organs that are often acquired from a CT or MRI scanner to diagnose disorders or direct medical treatments like surgical planning or experimentation. Radiologists, engineers, and doctors use medical image processing to learn more about the anatomy of specific individuals or populations. Figure 1 depicts the schematic representation of the proposed methodology.



**Figure 1: Schematic representation of the proposed methodology**

**A. Data collection**

An MRI scan dataset comprised 319 images from distinct individuals. BRAMSIT is made up of 319 images depicting a wide range of topics. Each subject is identified by a unique reference number, age, and an axial identifying number. There are many examples of normal scan pictures of BRAMSIT patients shown in Figure 2. Figure 3 depicts the aberrant and ground truth MRI scans of five individuals [11].



**Figure 2: Sample of MRI normal scan images**

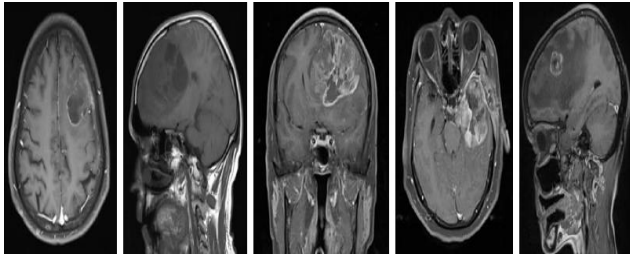


Figure 3: sample of MRI abnormal scan images

### B. Image processing using histogram equalization

Raw images are subjected to image preprocessing, which involves reducing abnormalities and enhancing significant aspects of the images so that they may be used in subsequent post-processing steps. The image preprocessing technique produced a set of  $n$  sub-histograms.  $[0 \ 255]$  is the range of the histogram of the images being used. We may begin by setting  $i_a$ , and  $r_a$  are also the weakest and greatest intensity values of the sub histograms of image  $D_k(W)$ , and the range of  $W - 1$  is  $[i_a, r_a]$ .

Generalized probabilities  $D_k(W)$  are applied to every individual histogram by the equation (1).

$$D_k(W) = D_{\max} \left( \frac{D(w) - D_{\min}}{D_{\max} - D_{\min}} \right)^{p_a} \quad i_a \leq w \leq r_a \quad (1)$$

Where  $p_a$  the accumulated probability density of the  $i$ th sub-histogram is,  $D_{\max}$  is the highest and  $D_{\min}$  is the lowest.

Following is an equation that normalizes the resulting weighted probabilities  $D_k(m)$ ,

$$D_{k_q}(m) = \frac{D_k(m)}{\sum_{m=0}^{h-1} D_k(m)} \quad (2)$$

A normalized weighted probability of input image histogram  $D_{k_q}(m)$  is often used.

Using the probability mass function of the input picture, histogram equalization generates a uniformly distributed histogram. The following equation is used to equalize each sub-histogram  $a$  with a range of  $[r_a - i_a]$ .

$$O_a(w) = i_a + (r_a - i_a) * T_{k_q}(m) \quad 1 \leq a \leq q \quad (3)$$

### C. Segmentation using Otsu threshold

The best method for separating an item from the backdrop of a picture is threshold segmentation. The histogram is divided into two portions, the target area and the background region, using an appropriate threshold between the object's lower grey level and the background's higher

grey level. To increase the contrast between the foreground and background areas, both components might be equalized independently.

Automated thresholding of probability shape-based images is done using Otsu's approach. As a normalized sum of two classes' variations, the Otsu approach seeks the threshold level that minimizes intraclass variance.

$$V_0 = \underset{V_c}{\text{ArgMax}} \{K_H(G(A_H) - G(A))^2 + K_Z(G(A_Z) - G(A))^2\} \quad (4)$$

The optimal threshold  $V_c$  is used in this equation. Underlying pictures  $K_H$ , as well as  $K_Z$ , is their PDF counterparts. For example, the mean image quality of  $A_H$  and  $A_Z$  is defined as  $G(A_H)$  and  $G(A_Z)$  whereas the average quality of the image is defined as  $G(A)$ .

### D. Feature extraction using the contour method

A histogram equalization step is required before contour extraction can begin. In general, historical traditions have low quality since the materials decay with time owing to factors such as storage conditions. As an independent variable, the active contour approach specifies a generalized function of "power" with a continuous curve that is made up of two terms: one for internal and one for external sources of energy. An image feature extraction that transforms into an intuitive function-solving method with exceptionally rigorous mathematical reasoning may be used to establish the goal boundary. Active contour models are also known as functional active contour models. Furthermore, significant structural changes, such as the splitting or merging of curves, cannot be implemented by these models. In this case, just one target profile may be derived. It is also difficult to extract the full return on investment (ROI) from brain images at one time because of the varying image contrast, thus it is required to complete the segmentation of numerous areas and combine certain post-processing techniques to complete ROI extraction.

### E. Feature selection using neighborhood components analysis

The process of selecting the best  $k$  features from among the dataset's features based on the algorithm's assessment results is known as feature selection. There has been a wide range of assessment criteria for feature selection approaches to date. Based on the learning technique utilized, these criteria are generally separated into two groups: dependent and independent. The NCA method, which relies on dependent

criteria, was used in our research to examine the impact of RBC characteristics on categorization. Algorithm selection is based on prediction and response values. In the method, the brain parameters were utilized as input parameters, and the best-discriminating parameters were grouped into a smaller set. The following are the specifics of how we arrived at the final list of features:

$$H = \{(y_1, y_1), \dots, (y_j, y_j), \dots, (y_K, y_K)\} \quad (5)$$

There are  $d$ -dimensional vectors, and there are  $K$ -dimensional vectors, and there is a  $K$ -class label for each of them. Weighting vector  $w$ , which may be used to determine the best feature set for closest neighbor classification, is a major purpose. The equation shows the weighted distance between two samples,  $v_a$ , and  $v_m$ , about the weighting vector  $K$ .

$$P_k(v_a, v_m) = \sum_{j=1}^b k_j^2 |v_{aj} - v_{mj}| \quad (6)$$

$w_m$  is the weight of the  $j^{\text{th}}$  feature, as shown in the figure. A kernel function  $k$  that yields big values for tiny  $k_j$  may be used to establish a link between the probability  $D_{am}$  and the weighted distance  $P_k$ . It is possible to define  $D_{am}$  as shown in the following equation (7).

$$D_{am} = \frac{w(P_k(v_a, v_m))}{\sum_{m=1, m \neq a}^q w(P_k(v_a, v_m))} \quad (7)$$

If  $a = m$ , then  $p_{am} = 0$ . This is how we get  $k_z = (\exp - \frac{z}{\sigma})$ , the kernel function looking for each point's likelihood of being picked as the reference point is affected by the kernel width. According to the equation,  $V_a$  likelihood of being correctly classified is equation (8).

$$D_a = \sum_m o_{am} p_{am} \quad (8)$$

#### F. Cognitive marine predators algorithm

As a way of gathering information on how marine predators hunt, CMPA has been developed. There are three periods in which marine predators and their prey move at various rates, which affects how well an MPA performs. In this phase, the prey is moving quicker than the predator can keep up with it. Two distinct phases:

Phase (i): When both the prey and the predator are traveling at about the same pace.

$$V_{am} = hr + \text{rand}(zr - hr) \quad a = 0 \dots q, m = 0 \dots d \quad (9)$$

Where, a population's,  $m$ -dimensional coordinates are represented by  $V_{am}$ , and  $n$  is the population size.  $d$  is the solution dimension. The search space's upper and lower bounds are  $zr$  and  $hr$ , respectively, and a random integer is a  $\text{rand}$ .

Phase (ii): When the predator is going faster than the prey. MPA has a worldwide search engine and a rapid convergence time.

$$\begin{cases} \text{stepsize}_a = \bar{B}_R \otimes (\text{Gh ite}_a - \bar{B}_R \otimes \text{Pr}\bar{e} y_a) \quad a = 1, \dots, q \\ \text{Pr}\bar{e} y_a = \text{Pr}\bar{e} y_a + D \cdot \bar{B} \otimes \text{stepsize}_a \end{cases} \quad (10)$$

In this case,  $\text{stepsize}_a$  denotes the step size. The normal distribution of Brownian motion generates a random number vector,  $\bar{B}_R$ , and  $\otimes$  the multiplicative operator is represented by  $\text{Pr}\bar{e} y_a$ .  $D$  is the step control factor is set at 0.5, and the random number generator generates  $\bar{B}$  from a distribution of values between 0 and 1. In this case, the current iteration number is  $\text{Iter}$ . The maximum number of iterations is  $\text{Max Iter}$ . There are three key drawbacks of MPA: the inability to build a varied starting population with high productivity, and the incapacity to explore the search area more generally and widely.

#### IV. RESULT AND DISCUSSION

In this paper, we proposed the CMPA for medical image processing. Accuracy, F1-score, recall, and precision are analyzed with proposed and existing methods. Existing approaches such as hybrid deep convolution neural network [HDCNN], multimodal deep guided filtering [MMDGF], deep neural network [DNN], and neutrosophic set [NS] are compared with the proposed method.

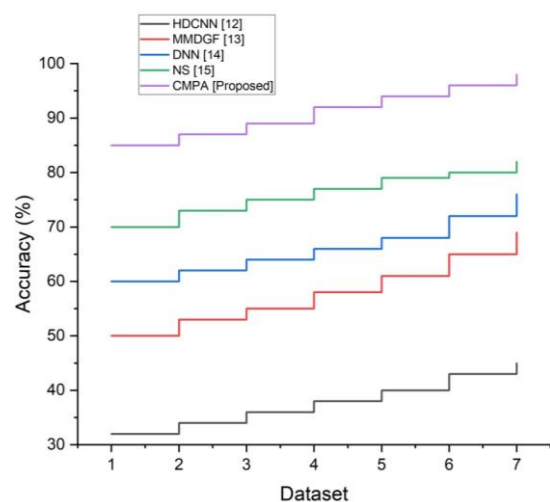


Figure 4: Comparison of the accuracy

Figure 4 depicts the comparison of the accuracy. The accuracy of a method is measured by utilizing a metric that considers a technique works effectively throughout all of its constituent parts. If every problem is equally important, this is a good thing. The value is determined by dividing the total number of ideas by the total number of true statements.

$$Accuracy = \frac{T_{positive} + T_{Negative}}{T_{positive} + T_{Negative} + F_{positive} + F_{Negative}} \quad (11)$$

The suggested work was found to be more accurate (98%) than the existing methods like HDCNN (45%), MMDGF (69%), DNN (76%), and NS (82%).

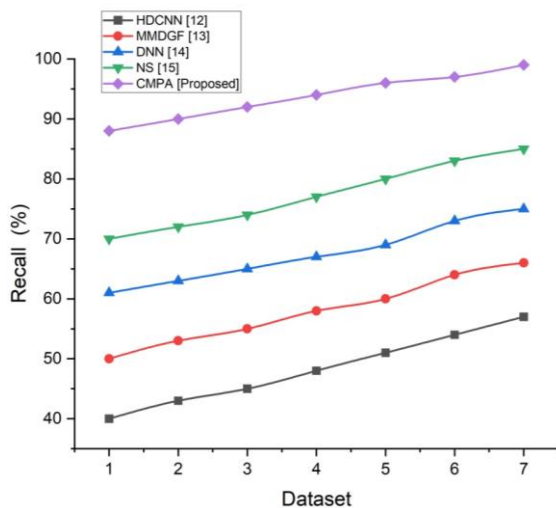


Figure 5: Comparison of the recall

Figure 5 comparison of the recall. In the medical image processing of information systems, recall assesses how successfully a suggested technique locates the supporting information that a person has desired to be returned to it. It has been determined that a set of measures in the following way:

$$Recall = \frac{True\ positive}{total\ number\ of\ actual\ positives} \quad (12)$$

The suggested work was found to be more recall (98%) than the existing methods like HDCNN (57%), MMDGF (66%), DNN (75%), and NS (85%).

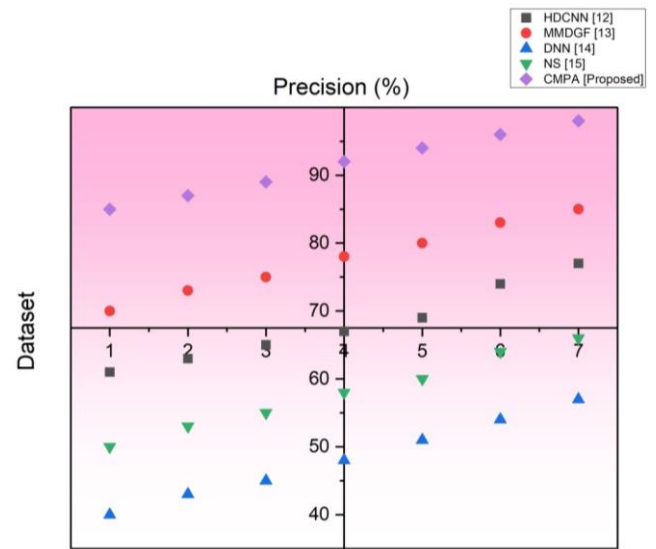


Figure 6: Comparison of the precision

Figure 6 depicts the comparison of the precision. Positive predictive value (PPV) is another term for a measure of accuracy. Precision is a metric for determining the number of correct class predictions out of a given sample. In other words, it's a measure of how well things went as opposed to how well they were projected to go. To find out how precise a measurement is, apply the formula below:

$$Precision = \frac{True\ positive}{Total\ predicted\ positive} \quad (13)$$

The proposed method CMPA shows more significance (98%) precision than the other existing methods like HDCNN (77%), MMDGF (85%), DNN (57%), and NS (66%).

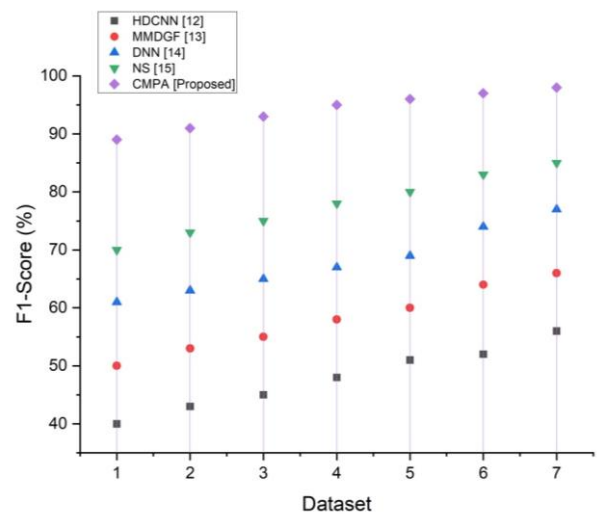


Figure 7: Comparison of the F1-score



Figure 7 depicts the comparison of the F1 score. Precision and recall are combined in the F1-Score. It's sometimes referred to as the "frequency mean" since it's the average of the two. Another approach to determining an "average" of numbers, the harmonic mean is often touted as being more suited for ratios (such as precision and recall) than the standard statistical distribution. Throughout this investigation, the proposed work CMPA has more f1-score (98%) than the existing methods like HDCNN (56%), MMDGF (66%), DNN (77%), and NS (85%).

### Discussion

Due to the general limitations of the existing method, figures clearly illustrate that the proposed methodology improves the existing one. The disadvantages of the current techniques are as follows. The proposed method is compared to the existing methods like hybrid deep convolution neural network [HDCNN], multimodal deep guided filtering [MMDGF], deep neural network [DNN] and neutrosophic set [NS] are more efficient for the CMPA for medical image process. The HDCNN quality of the medical image process was impacted by the usage of more images than was necessary. Generally, the MMDGF image should be decoupled from the processed output to minimize the impact of the adversary approach on the guidance image. DNN-based medical image analysis is vulnerable to a wide range of assaults; however, the changes to the classifier are so minor that they have limited effect on the diagnosis outcomes when medical specialists are engaged. The great throughput and imprecise handling capabilities of neutrosophic set-based algorithms have garnered interest in tackling image processing tasks. As a result, the method for medical image processing developed by the CMPA is more effective.

### V. CONCLUSION

In this paper, the field of medical image processing, areas such as illness identification, segmentation, detection, and image normalization have benefited greatly from the fast-evolving technology. The paper proposed CMPA for medical image processing regarding brain tumor classification. This research analyzes 319 images from the BRAMSIT database. Histogram equalization is used to image preprocessing, Ostu threshold is used for segmentation, contour method is used for feature extraction, and neighborhood components analysis is used for feature selection. The experimental results are provided as accuracy (98%), recall (99%), precision (98%), and F1 score (98%). The suggested approach has higher efficiency than the

existing methods. If we analyze more results in the future, then the performance of this research will be increased effectively.

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