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6. Conclusion

This research presents a novel method for distinguishing brain cancers using a precise and effective model. To achieve a satisfactory model, it is important to employ advanced processing stages such as the median filter, data magnification, and configuration. The presented methods encompass a wide range of techniques, ranging from dry waveform manipulation to the extraction of brain features from MRI scans. A portion of the photographs in the collection have been resized to optimize efficiency and cost-effectiveness. The Bat Algorithm has been augmented with Convolutional Neural Network (CNN) functionalities. Compared to all other similar functions, the recommended approach demonstrated exceptional accuracy in categorization. The study utilized data from the complete brain imaging in addition to the Brain Tumor dataset. The Bat Algorithm achieved an accuracy of 95.3%, the Convolutional Neural Network Algorithm achieved an accuracy of 92.4%, and the bat algorithm and CNN achieved an accuracy of 99.7%. In the future, another type of artificial intelligence could be utilized to enhance precision and speed of performance. Several photographs in the collection have been resized to be more efficient in terms of time and cost.

images from 55 patients with meningioma, and 998 MRI brain images from 88 patients with glioma. Every image was offered MATLAB files and measured 512 by 512 pixels. The second batch of data consists of 430 typical pictures of the brain. There are 142 brain MRI pictures in the third data set.

5.1. Performance evaluation

In this paragraph, explain of Performance evaluation of cancer brain

5.1.1. Accuracy

The accuracy of separation models is typically assessed, and this is seen to be one of the most crucial factors. It is described as an accurate approximation of the whole value of the forecast. If a set of uneven data is skewed toward a class with a significant sample size, there is a possibility of high accuracy. Every test case is unique. A significant condition separator that upholds the accuracy of half of the most prevalent labels in the test set is given the primary category. From now on, a scale is used to measure precision (4)

$$\text{Accuracy}=\sum i=11(TPi+TNi)TPi+TNi+FPi+FNi \tag{4}$$

5.1.2. Precision

Equation displays the precision of the macro-intermediate (5)

$$\text{Precision}=\sum i=11(TPi)/(TPi+FPi) \tag{5}$$

5.1.3. Recall

The technique of determining each class recall, which is also necessary to determine overall recall, is known as the macro-average. The average value is then stated as (6)

$$\text{Recall}=\sum i=11(TPi)/(TPi+FNi) \tag{6}$$

  - Fine-tune the CNN model by adjusting the hyperparameters and architecture based on the validation performance

Step 6: Evaluation and Performance Comparison

- Evaluate the performance of the BA-CNN approach on a held-out test set:
  - Calculate metrics like accuracy, precision, recall, and F1-score
- Compare the performance of the BA-CNN to other feature selection and classification techniques, such as:
  - CNN without feature selection
  - Other feature selection methods (e.g., PCA, LDA, IG) combined with CNN
  - Alternative hybrid approaches (e.g., GA-CNN, PSO-CNN)

Step 7: Deployment and Real-world Application

- Once the BA-CNN model has been thoroughly evaluated and its superior performance is confirmed, it can be deployed for real-world brain cancer detection tasks.
- The trained model can be integrated into a clinical decision support system or used for automated screening of brain cancer images.

5. Results & discussion

Three different kinds of data are used to classify brain tumors. The accessible website was the first Open Source site. The whole brain atlas's image collection is available in the second database. The Brain tumor website is where the images from the third set of data were gathered. In the first database of 2057 T1-weighted MRI brain scans, 150 cases were treated for pituitary, glioma, and meningioma brain tumors. In this instance, it had 630 MRI brain tumors of the pituitary gland from 42 patients, 504 MRI brain

Step 3: Bat Algorithm for Feature Selection

- Initialize the Bat Algorithm parameters:
    - Population size (number of bats)
    - Frequency range
    - Pulse rate
    - Loudness
- For each iteration of the BA:
    - Generate new bat positions (candidate feature subsets) based on the current position, frequency, and velocity
    - Evaluate the fitness of each bat's feature subset using a suitable metric (e.g., classification accuracy)
    - Update the global best feature subset found so far
    - Adjust the pulse rate and loudness based on the BA rules
    - The final output of the BA is the optimal feature subset that maximizes the classification performance.

Step 4: CNN Architecture Design

- Construct the Convolutional Neural Network architecture:
    - Define the number and types of convolutional, pooling, and fully connected layers
    - Specify the hyperparameters, such as filter sizes, strides, and activation functions

Step 5: CNN Training and Fine-tuning

- Train the CNN model using the brain cancer image dataset:
    - Use the optimal feature subset selected by the Bat Algorithm as the input to the CNN
    - Apply techniques like data augmentation, regularization, and early stopping to prevent overfitting

Step 11:if ((rand < Ai) and (F (Xi) < F(Gbest)): If Loudness A is less than the randomly assigned number, and if the objective function of the new solution remains lower than the objective function of the best global solution.

Step 12:Accept the new solutions, Increase ri and reduce Ai: These new solutions are accepted r, increasing the pulse rate and decreasing the loudness A, .

Step 13:Find the current Gbest: The current solution is compared with the current global best, solution if the current solution is better it becomes the new Gbest.

Step 14:The last simple loop which is similar to the previous one but has different names of the input parameters END OF THE MAIN LOOP.

4.5. CNN Classification

Training and fine-tuning of the CNN architecture is accomplished by making use of the optimum feature subset that was chosen by the BA.The CNN is able to learn the hierarchical characteristics and patterns from the images of brain cancer, which are subsequently utilized for the ultimate categorization of cancer instances as opposed to cases that do not involve cancer.

Step 1: Data Preprocessing

- Collect the brain cancer image dataset
- Preprocess the images, e.g., resize, normalize, and apply data augmentation techniques

Step 2: Feature Extraction

- Extract the initial set of features from the preprocessed brain cancer images
- This can be done using techniques like Gabor filters, color histograms, or pre-trained CNN features

Step 2:Define frequency Fi and velocity Vi: The frequency F and velocity V are then set to zero with a frequency at which any of the links that shall connect at: & an initial velocity at a at which the link shall move at.

Step 3:Initialize pulse rates ri and the loudness Ai: Here it is presupposed that the pulse rates r and the loudness A are equal to some random integer values.

Step 4:while t < Maximum iterations do: This is the final stage of preparation, the central section of the gene expression programming algorithm, in which all calculations are mad

Step 5:Update frequency and velocity: The frequency and speed is as follows The following equations are used to model whether or not these requirements have been met: For the 'business as usual', scenario GHG emissions are forecast to rise at a growing rate over the next three decades.

Step 6:It can be quite possible to approximate the transfer function values of a specific clinical trial using the following equation. 2: As for the computation of the transfer function f_i, this can be done with the aid of the equation The characteristics of the H(f) function are discussed in the next section.

Step 7: update Vi, Xi as well as Fi as given in the following equitation 3 to 4

Step 8:if (rand > ri): This predicate is used to check if a randomly generated number m is greater than all the other values in the clinical data set including the pulse rate r.

Step 9:Select the global best solution (Gbest): Therefore, from all the individual global best solutions identified in the sites, the Gbest is selected and the dimensions of the X are shuffled randomly with the help of the global best.

Step 10: Generate new solution randomly Eq (5): The new solutions are entered following the predetermined equation from randomly generated numbers.

4.4. Feature Selection Using Bat Algorithm

Enhancing some brain cancer images can facilitate the development of bat algorithms or algorithms that draw inspiration from bats. To enhance simplicity, we currently employ the subsequent approximate or standard regulations:

a) All bats utilize echolocation to perceive distance, and they possess an innate ability to distinguish between food/prey and obstacles;

b) Bats have random flight patterns, moving at a velocity vi from point xi. They maintain a constant frequency fmin, but their wavelength λ and loudness A0 change as they look for prey. These entities have the ability to autonomously modify the wavelength (or frequency) of the pulses they emit and vary the rate at which they emit pulses, denoted as $r \in [0,1]$, based on the closeness of their target.

c) While the loudness can exhibit various fluctuations, make the assumption that the range of loudness spans from a positive value A 0 to a significant constant value Amin.

Furthermore, it is important to note that the estimation of time delay and three-dimensional topography does not include the use of ray tracing. While this feature may have potential benefits for the application in computational geometry, we have decided not to implement it due to its increased processing complexity in multidimensional scenarios. Furthermore, we employ the subsequent approximations for the sake of simplicity, in addition to the aforementioned simplified assumptions. Typically, the frequency f within a range [fmin,fmax] corresponds to a range of wavelengths [λmin,λmax].

Step1 :Initialize Bat population: The seeds of the random number generators for X zero are set initially to a random value between the specified lower and upper limits.

c) Create multiple key points:
   - If multiple dominant orientations are detected, create multiple key points with those orientations

Step 4. Key point descriptor calculation:

a) Define a local neighborhood:
   - Consider a 16x16 pixel area around the key point

b) Compute gradient magnitude and orientation:
   - Calculate the gradient magnitude and orientation within the local neighborhood

c) Create a histogram of orientations:
   - Divide the local neighborhood into 16 4x4 subregions
   - Create a histogram of gradient orientations for each subregion

d) Generate descriptor vector:
   - Concatenate the histogram values from all subregions to form a 128-dimensional descriptor vector

e) Normalize the descriptor vector:
   - Normalize the descriptor vector to ensure robustness to illumination and contrast changes

Step 5. Key point matching and verification:

a) Compare descriptors:
   - Calculate the distance between key point descriptors from different images

b) Apply a matching criterion:
   - Set a distance threshold to identify potential matches

c) Perform additional verification:
   - Apply techniques like outlier rejection or geometric verification to enhance the accuracy of the matches

Step1. Scale-space extrema detection:

a) Construct a Gaussian scale-space pyramid:
  - Convolve the input image with Gaussian kernels of varying standard deviations
  - Store the resulting blurred images in the scale-space pyramid

b) Compute the Difference-of-Gaussian (DoG) pyramid:
  - Subtract adjacent Gaussian-blurred images to create the DoG pyramid

c) Identify local extrema in the DoG pyramid:
  - Compare each pixel in the DoG pyramid to its 26 neighbors
  - Mark pixels that are local maxima or minima as potential key points

Step 2. Keypoint localization:

a) Eliminate unstable keypoints:
  - Discard keypoints with low contrast or poor localization

b) Compute keypoint location and scale:
  - Refine the location and scale of each remaining keypoint

Step 3. Orientation assignment:

a) Compute gradient magnitude and orientation:
  - Calculate the gradient magnitude and orientation at each keypoint location

b) Assign dominant orientation:
  - Create a histogram of gradient orientations in a neighborhood around the key point
  - Assign the dominant orientation as the peak in the histogram

standardizing the image via the Min-Max Normalization Technique, and employing SIFT to extract distinctive attributes. The choice of the bat algorithm and classification procedure is determined by the Convolutional Neural Network (CNN).

Output Pixel Value = (1/(k * k)) * Σ(Input Pixel Value)

where:

Output Pixel Value is the filtered value of the pixel.

Input Pixel Value is the value of the pixel within the kernel window.

k is the size of the kernel, and k * k represents the total number of pixels within the kernel window.

The sum Σ is taken over all the pixels within the kernel window.

4.3. SIFT Feature Extraction

SIFT (Scale-Invariant Feature Transform) feature extraction can be applied to an image of a brain tumor to identify distinctive local features. The algorithm works by detecting key point locations at multiple scales, refining them through localization, assigning orientations to capture rotational invariance, and calculating descriptors that encode the appearance and structure of the regions around the key points. These descriptors can then be used for tasks such as feature matching or object recognition. By performing SIFT feature extraction on the brain tumor image, we can extract meaningful and scale-invariant features that enable robust analysis and comparison of tumor characteristics across different images. In the below algorithm steps to step SIFT:

4.1.Stander Dataset

This dataset is an amalgamation of three distinct datasets: figshare, SARTAJ dataset, and Br35H.This dataset has 7023 human brain MRI scans that have been categorized into four classes: glioma, meningioma, no tumor, and pituitary.The brain tumor MRI dataset can be found at the following link: https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor

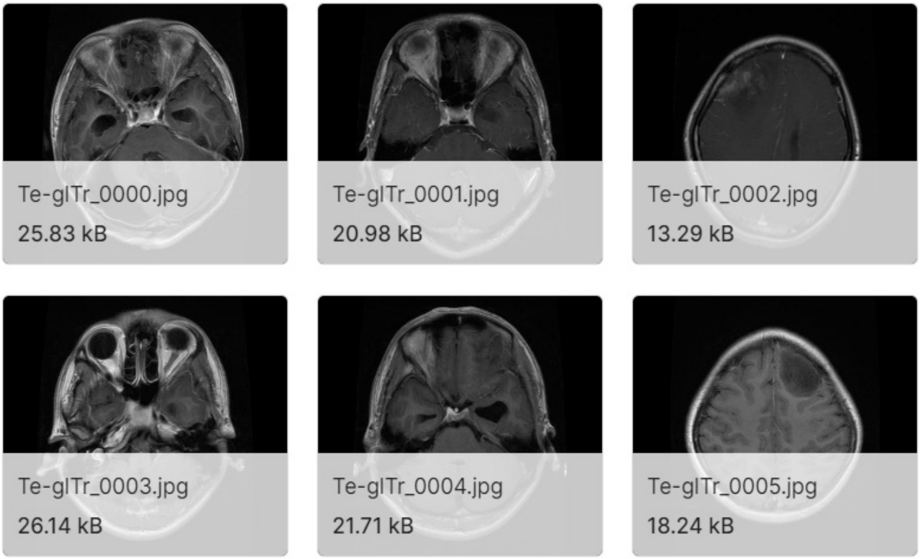

Figure 3. Sample of stander dataset.

4.2. Pre-Processing Using Mean Filter

The pre-processing procedure aims to enhance the efficiency and characteristics of Magnetic Resonance Imaging (MRI) images. This stage enhances the process of classification and is employed by autonomous professionals for subsequent analysis. The procedure entails generating a cerebral image by the utilization of a mean filter, incorporating a dataset, microbat in the jth iteration, A stands for loudness and r_ij is a random number of between 0 and 1 and lastly, X^ * represents the OPTI, or best solution found to date in the search space.

$$y(j) = y(j-1)v_i \quad (3)$$

There are two main mathematical equations used in the Bat Algorithm; the first updates the position, speed, and frequency of each microbat in each iteration, in a bid to converge on the optimal solution in the search space.

4. Proposed Methods

The implementation of the proposed Bat Algorithm and Convolutional Neural Network (CNN) function improves segment effectiveness in the identification of brain tumors. MATLAB is less in time and more in speed and processing power as compared to C language. The function involves three stages: Pre-processing, Feature extraction, Feature Selection, and Classification of B-CNN. The computer assists in diagnosing brain tumors.

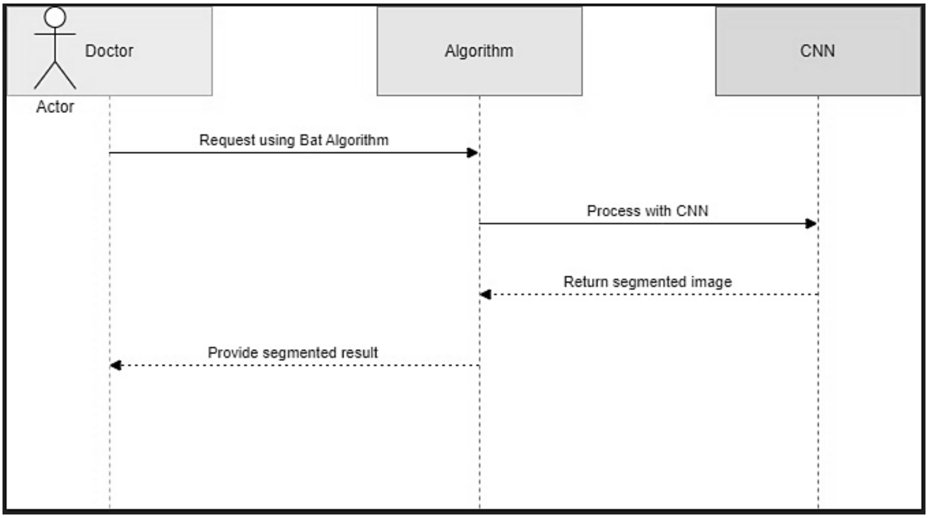

Figure 2 .Sequence Diagram of Proposal Method

performance rather than existing traditional methodologies. While this work by [18] does not employ the Bat Algorithm or utilize deep learning for the diagnosis of brain cancer, it contains valuable information on other aspects of adversarial learning which may be useful in medical image processing in the future.

For feature selection, the authors [19] employ a Bat Algorithm technique and for the detection of brain tumors, they use a deep learning model and found improved efficiency in the integrated process as compared to the individual application of both the techniques.

This review by [20] is on the employment of emerging algorithms, specifically, the Bat algorithm, and utilization of various optimization features that may be useful while choosing features.

3. Bat Algorithm

The Bat Algorithm utilizes the behaviors and characteristics of microbats for optimization purposes. It operates in a multidimensional search space, where each microbat represents a potential solution. The position and speed of each microbat are updated iteratively. Equation (1) describes the frequency of each microbat. Within the range of [f_min, f_max], f_i represents the frequency of the ith microbat.

$$f_i = f_{min} + \mu(f_{max} - f_{min})\beta\beta \, \epsilon[0,1] \qquad (1)$$

Equation (2) shows the speed update equation of the every microbat during the jth iteration. Here, for i equal to 1:m, v_ij represents the speed of the ith microbat in the jth iteration, v_0 is the initial speed, and n_iter is the total number of iterations. $f_i = f_{min} + \mu(f_{max} - f_{min})\beta\beta \, \epsilon[0,1]$.

$$v_i(j) = v_i(j-1) + \mu\left(fx_{(j)} - x^{OPTI}(j)\right) \qquad (2)$$

Equation (6) shows how each of the microbats' positions in the jth iterations are computed. In this case, x_ij is equal to the position of the ith networks. In the following study [10], a new model that combines both the CNN and the Bat Algorithm for selecting the relevant features to improve the results of the classification of brain tumors will be proposed.

The authors [11] conclude the overall procedure of using the Bat Algorithm for feature selection in combination with a deep learning model for the classification of brain tumors and, identify why this synergistic approach works.

in [12] the application of the Bat Algorithm in feature selection and prognosis of brain tumors is proposed and the results will be tested with a deep neural network to determine a better result of the test.

The authors [13] introduced an optimal feature selection using the Bat Algorithm and used deep learning to enhance the efficiency of detection of brain tumors as evidenced by the findings of the study.

Although this work [14] does not outline specific methods for diagnosing any form of brain cancer, it gives details of different EOAs about feature selection and recommends the Bat Algorithm for similar tasks.

Therefore, this research [15] will focus on the idea of integrating the Bat Algorithm to perform feature selection task on the brain MR images and the deep learning model to classify brain tumors in order to demonstrate the modification and improvement of the new hybrid model.

It is crucial to observe that the authors present a new approach in this study [16], which incorporates the Bat Algorithm into a deep neural network for diagnosing brain tumors, explaining the performance enhancement observed in this research work.

The primary objective of this [17] is to analyze the capability of utilizing the Bat Algorithm for feature selection and integrate it with the Deep learning models for Brain Tumor Classification to determine its effectiveness in terms of

2. Related Work

In this paragraph, we talk about a group of previous research that deals with the bat algorithm and deep learning to detect brain cancer.

In their study [7] aimed at the identification of the early signs of dementia using the improved BAT optimization algorithm to segment the different subregions of the brain as well as utilizing deep learning to classify the identified subregions. For segmentation in this study, the technique utilizes histogram equalization and Otsu's thresholding as pre-processing methods and the BAT optimization algorithm and, the improved BAT algorithm. Here the authors used the convolutional neural network for classification which leads to enhanced segmentation and adequate classification.

In this regard, for new automatic CMB diagnosis method [8] suggested the utilization of deep learning and optimization algorithm. The input of the method is brain MRIs, and the outputs are CMB and non CMB findings. It employs sliding windows for the formation of the dataset, the VGG pre-trained for image features, and the ELM trained via GBA. The method is shown to be more accurate and has higher generalization performance compared to several other existing methods.

This study [9] presents a performance-optimized CNN classifier through a novel BFOA-LA hybridization method. The performance analysis of the developed classifier clearly indicates that the proposed BFOA LN-CNN produced higher accuracy than the existing DCNNs with reference to the G-HHO and IIB-based Deep Residual network models. The method attains an accuracy of 99 percent in classifying the personalized data. 41% outperforms the DCNN G, HH & O architectures as well as IIB deep residual neural

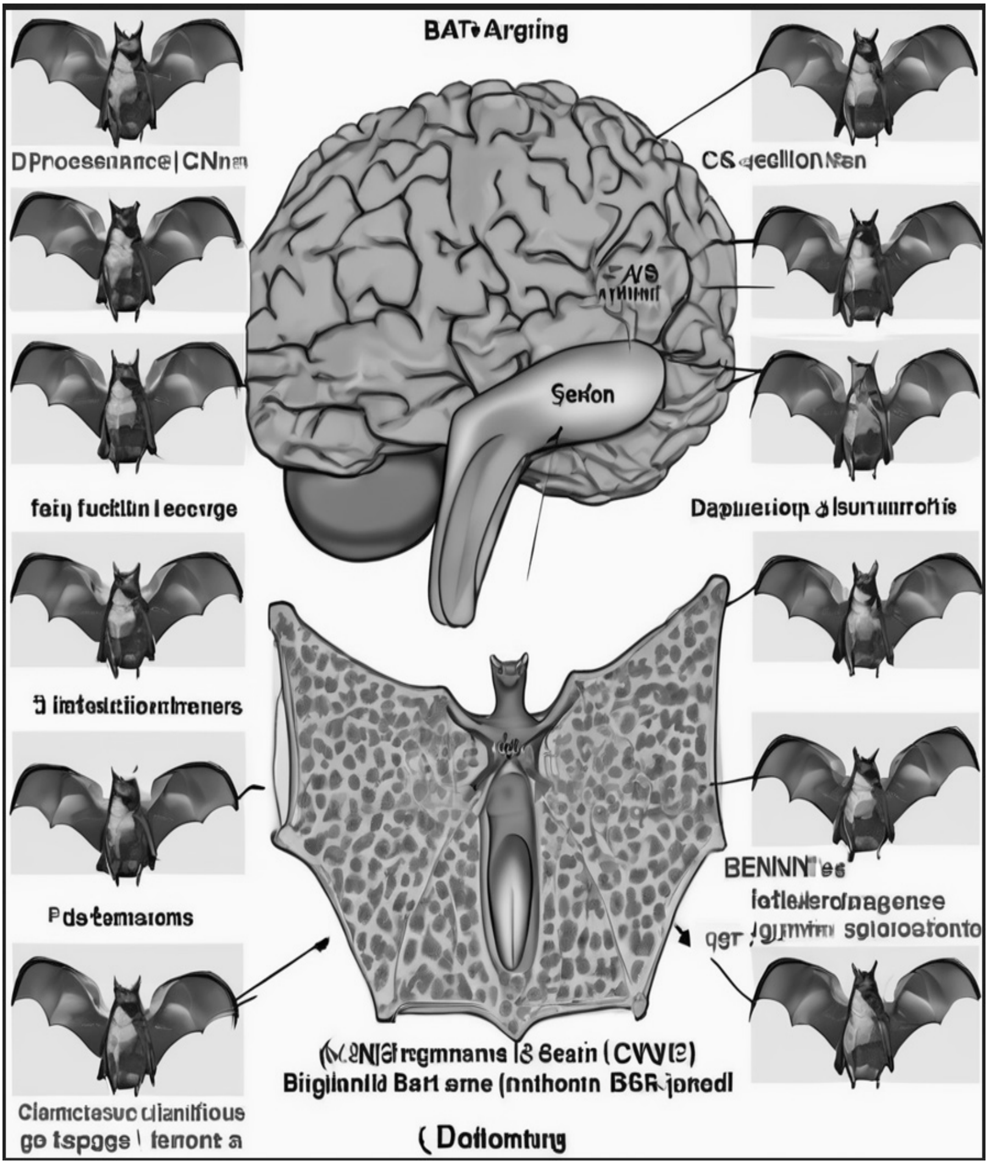

Figure 1. Bat Algorithm With CNN [6].

optimization of the feature selection, this means that the algorithm aims at selecting the most disciplined features from the input MRI brain images. These selected features are then used to train a deep learning model, for instance, Convolutional Neural Network, for the classification between brain cancer and the normal one.

The contributions of this study can be summarized as follows: In the light of the above facts, the following are the contributions of this study:

1. Suggest an improved method of using the Bat algorithm and deep learning in selecting relevant features and diagnosing brain cancer and neutralize the blind spots of the two methodologies.
2. An investigation of the proposed approach based on the MRI and CT brain image datasets accessible to the public will provide a reliable judgment of how effective the proposed solution is to feature extraction and classification in contrast to conventional methods.
3. Satisfying the most critical question in this study of how the Bat Algorithm for feature selection plays significant role in the final performance and usability of Deep Learning model.
4. Delineate how incorporating of Bat Algorithm and the deep learning for the detection of brain cancer can be advantageous with respect to clinical practice and potential future enhancements of this study.

Many state-of-the-art issues in the medical image analysis enhance in the recent past fourty years owing to the contribution of deep learning techniques [3]. Doctors have also noted that using CNNs and other architectures from the deep learning family, they are able to identify relevant features from Medical images for classification tasks [4]. However, such deep learning models show decent performance but they are more sensitive to the input features chosen and the quality of data they are fed on.

Feature selection being one of the first steps in the preprocessing process of data for the learning pipeline in designing deep learning, models occupies a very important place to not only improve the performance of the feature selection process, but also the interpretability of the models. Here, feature selection is an integral part of learning significant representations because it enhances learning methods by identifying only the most relevant features out of the available input to enhance the accuracy, generalization, and computational proficiency of a specific model [5].

Another relevant approach to performing the feature selection is the methods within the bio-inspired optimization algorithms, specifically Bat Algorithm (BA) [6]. Bat Algorithm is a meta-optimization technique that has its root in echolocating nature of bats and particularly in the search of feature set for a particular problem. Integrating the Bat Algorithm with deep learning models is advantageous to brain cancer diagnosis systems because of the integration of elements of the two ways.

Here in this paper, a meta heuristic algorithm known as Bat Algorithm and deep learning technique is presented to select the best features and categorize an image in to having brain cancer or not. The above method is then used as follows: The Bat Algorithm is initially employed to compute the

1. Introduction

Brain tumors present a formidable challenge as they exhibit a high mortality rate and involve the aberrant growth of brain cells. The categorization of tumor cells is contingent upon their level of aggressiveness, with those exhibiting a heightened risk factor being classified as either at risk or as having cancer. In order to detect and treat the tumor, patients are required to undergo a number of tests, with the most frequently used imaging techniques being computed tomography (CT) and magnetic resonance imaging (MRI). MRI is regarded as an excellent brain imaging technique because of its ability to provide clear differentiation between soft tissues and its non-invasive nature [1][2].

Brain tumors are divided into two types: harmful and harmful. The World Health Organization (WHO) has issued a widely used grading system, which divides brain tumors into grades I to IV under a microscope. Grade I and grade II are benign brain tumors, while grade III and grade IV are high-grade brain tumors. Undiagnosed brain tumors may degenerate into high-grade tumors if not treated properly. The correct and timely identification of Brain Cancer is one of the most critical problems in today's world of medicine and determines the further outcomes of diseases and the efficacy of the treatment process in most cases. The conventional methods that entail detection of anomalies through the interpretation of medical images by qualified radiologists have drawbacks such as lacking well-defined objective and often subjective outcomes, requiring a lot of time and entailing high inter and intra observer variabilities. Particularly, there is more attention paid to the approaches for creating complicated systems that would improve the possibility of determining and classifying the signs of a brain cancer at the initial stage.

المستخلص

يعتبر سرطان الدماغ من أخطر الأنواع التي يجب علاجها في أسرع وقت ممكن. ولذلك فمن الضروري الكشف عن سرطان الدماغ في مراحله المبكرة لتعزيز تشخيص الحالة. تقترح هذه الدراسة الجمع بين خوارزمية الخفافيش (BA) وطرق التعلم العميق لتحديد وتصنيف أورام المخ في الصور الطبية بدقة.

في هذا البحث، تم استخدام خوارزمية الخفافيش لاختيار السمات المميزة من صور الدماغ المدخلة. خوارزمية الخفافيش (BA) هي خوارزمية تحسين ميتايورستية تحاكي سلوك تحديد الموقع بالصدى للخفافيش. يستكشف مساحة الميزات بكفاءة لاكتشاف الميزات الأكثر ملاءمة للتحليل، وهو أمر مفيد ويوظف هذه الميزات لتدريب شبكة عصبية اصطناعية متقدمة بشكل استثنائي (ANN)، الشبكة العصبية التلافيفية (CNN)، التي تعمل على تحسين تصنيف أنسجة المخ السرطانية من الأنسجة الطبيعية. علاوة على ذلك، يمكن لنموذج التعلم العميق أن يصور بدقة الأنماط غير الخطية المعقدة داخل البيانات، مما يعزز القدرات التشخيصية.

تم إجراء سلسلة من الاختبارات باستخدام التصوير بالرنين المغناطيسي والأشعة المقطعية المتاحة بسهولة والتي تم الحصول عليها من المجال العام. إن الجمع بين خوارزمية الخفافيش ونموذج التعلم العميق يتفوق على التقنيات المستخدمة سابقًا لاستخراج ميزات أورام المخ وتصنيفها، مما يؤدي إلى اكتشاف أكثر دقة. وقد لاحظنا تحسناً من حيث الدقة والحساسية والانتقائية مع وصول الدقة

كلمات مفتاحية: مرشح الوسط، خوارزمية الخفافيش، الشبكة العصبية الاصطناعية (ANN)، الشبكة العصبية التلافيفية (CNN)

Abstract

Brain cancer is considered one of the most dangerous types that must be treated as soon as possible. Therefore, it is necessary to detect brain cancer in its early stages to enhance the diagnosis of the condition. This study proposes to combine the bat algorithm (BA) with deep learning methods to identify and classify brain tumors in medical images accurately.

In this paper, the bat algorithm was used to select distinctive features from the input brain images. The Bat Algorithm (BA) is a metaheuristic optimization algorithm that mimics the echolocation behavior of bats. It efficiently explores the feature space to discover the most suitable features for analysis, which is useful and employs these features to train an exceptionally advanced artificial neural network (ANN), the Convolutional Neural Network (CNN), that improves the classification of cancerous brain tissue from normal tissue. Furthermore, a deep learning model can accurately depict complex nonlinear patterns within data, enhancing diagnostic capabilities.

A series of tests were performed using readily available MRI and CT scans obtained from the public domain. Combining the bat algorithm with a deep learning model outperforms previously used techniques for feature extraction and classification of brain tumors, leading to more accurate detection. We have noticed an improvement in terms of accuracy, sensitivity, and selectivity, with accuracy reaching

Keywords: Mean Filter, Bat Algorithm, Artificial Neural Network (ANN), Convolutional Neural Network (CNN)

Exploring the Benefits of Feature Selection based on bat algorithm and deep learning in Brain Cancer Diagnosis

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استكشاف فوائد اختيار الميزات بناءً على خوارزمية الخفافيش والتعلم العميق في تشخيص سرطان الدماغ

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