ISSN NO: 2770-4491
Date of Publication:24-11-2023

Precise Classification of Brain Magnetic Resonance Imaging (MRIs) using COOT optimization

Dheyaa Jabbar Luaibi
Work place: Prime Minister's Office
Email: hejdjdjjdjdjdj7@gmail.com

Abstract

This research demonstrated a hybrid approach that combined machine learning algorithms with expert medical knowledge to achieve precise classification of brain MRIs. By harnessing the capabilities of artificial intelligence, these computer-aided methods have the potential to assist healthcare professionals in making well-informed decisions, leading to better patient outcomes. One of the primary advantages of computer-aided diagnosis is its ability to rapidly and efficiently analyze large volumes of medical data. This technology can process numerous MRI scans in a fraction of the time it would take for a human expert to review them individually. This not only saves valuable time but also minimizes the risk of human error or oversight. Furthermore, computer-aided diagnosis systems can detect subtle patterns or abnormalities that might elude even the most experienced radiologists. By analyzing thousands of MRI images and comparing them with established patterns associated with different diseases, these systems can identify potential indicators that might be missed by human observers alone. This heightened accuracy can significantly enhance early detection rates and facilitate timely intervention, ultimately saving lives. The proposed classification system utilized GLCM to extract a comprehensive set of features that capture the spatial relationships between pixels in an image. These features effectively represent significant patterns and structures in the image, thereby facilitating accurate classification. Additionally, the approach incorporated COOT optimization, an optimization technique, to enhance the feature extraction process beyond mere feature selection. By leveraging a cooperative and coordinated framework involving multiple agents, the variables were fine-tuned, leading to improved quality in the extracted features. Consequently, this approach achieved superior feature extraction results, yielding better and more precise features for a given image. Subsequently, CNNs were employed for image classification by training a deep neural network on a labeled dataset and optimizing its parameters. Leveraging the learned patterns and features from the training data, the trained model exhibited the ability to classify new images, resulting in enhanced accuracy for MRI classification.

Keywords: Magnetic Resonance Image (MRI), Haar Wavelet Transform(WT), COOT, Convolutional Neural Network(CNN).

Introduction

MRI scans are highly effective in diagnosing brain tumors and monitoring patients' health. However, they can be expensive and time-consuming, limiting accessibility for certain individuals or regions with limited healthcare resources. To overcome this challenge, researchers and medical professionals are continuously working towards developing alternative detection techniques that are more affordable, accessible, and efficient. One promising approach is the integration of artificial intelligence (AI) algorithms with imaging data. By training AI models on extensive datasets of MRI images from patients with brain tumors, these algorithms can learn to detect patterns and anomalies that may indicate the presence of a tumor. This technology holds significant potential in assisting radiologists and clinicians in accurately diagnosing brain tumors at an early stage. AI-powered detection techniques offer several advantages over traditional methods. They are non-invasive, eliminating the need for invasive procedures, and they require less time compared to traditional diagnostic approaches. These algorithms can rapidly analyze large volumes of imaging data, providing reliable results that enable timely intervention and treatment planning. In addition to AI-based approaches, advancements in molecular imaging techniques have also contributed to improving early tumor detection. These techniques utilize specialized imaging agents to identify molecular markers associated with tumor growth and progression, providing valuable insights for early diagnosis and treatment optimization.

ISSN NO: 2770-4491
Date of Publication:24-11-2023

By harnessing the power of AI algorithms and innovative imaging techniques, healthcare professionals can enhance their ability to detect brain tumors accurately, enabling early intervention and improving patient outcomes. The wavelet transform can be utilized in the preprocessing stage of MRI (Magnetic Resonance Imaging) image analysis. It can be applied in the preprocessing stage to get rid of MRI images often contain noise that can affect the accuracy of subsequent analysis. Wavelet de noising techniques, such as wavelet thresholding, can be employed to reduce the noise while preserving important image features [1-3]. The transform decomposes the image into different frequency bands, allowing the identification and removal of noise components at specific scales. In this paper using Haar wavelet in denoising stage. The Haar wavelet transform is a technique used to divide an image into different levels of detail and approximation, helping to reduce and remove noise from the image. It involves partitioning the image into smaller regions or scales and calculating the details and approximations at each level. The details capture rapid changes in illumination or color, while the approximations represent more balanced and similar patterns. By iteratively performing this process and utilizing the results from higher levels, the image is gradually decomposed. The Haar wavelet transform can be used to analyze the image, enhance its quality, and increase its clarity by reducing or eliminating noise. Secondly, in extracting traits to extract features from MRI. Feature extraction using GLCM in brain MRI images is a critical step in medical image analysis. It transforms MRI images into analyzable features for accurate diagnosis of neurological diseases. GLCM calculates statistical relationships between pixels, extracting features like energy, contrast, and texture. These features differentiate tissues, identify abnormalities, and aid in treatment planning. Feature selection plays a crucial role in data mining, machine learning, and pattern recognition, with the goal of reducing dimensionality and improving classification accuracy. Optimization techniques, such as coot optimization, are commonly employed to identify the optimal subset of features. In image analysis, the careful selection of features is essential for tasks like object recognition and characterization, where discriminative visual cues are key. This process not only enhances accuracy but also improves efficiency in these tasks. The study was dedicated to developing an automated system for detecting brain tumors using Statistical Classification Methods. The training phase focused on distinguishing between normal and abnormal MRI scans. The classifier learned patterns that indicated abnormalities, enabling precise classification of new scans. Convolutional Neural Networks (CNNs) were utilized to categorize scans as either having a tumor or being tumor-free, analyzing extracted features and predicting the presence of tumors [4-6].

Related Work

1- Osman, Özkaraca, Okan [7]

The study focuses on developing a novel deep learning model for brain tumor classification using MRI images, leveraging open-source data from Kaggle. It combines advantages from transfer learning methods (DenseNet, VGG16, basic CNNs) while addressing their drawbacks. The proposed model exhibits enhanced classification performance, though with increased processing time. Future improvements aim to address this limitation and incorporate tumor segmentation for precise localization and size determination in the brain. achieving a 98.62% accuracy rate.

2- Muhammad, Hameed, Siddiqi [8]

An Enhanced Machine Learning Approach for Brain MRI Classification" highlights the pressing need for a swift and dependable classification system for diverse brain diseases through MRI analysis. The proposed method employs global histogram equalization to eliminate unnecessary details, utilizes symlet wavelet transform for feature extraction, employs linear discriminant analysis (LDA) to minimize feature dimensions, and employs logistic regression for training and evaluation. Achieving a remarkable 96.6% accuracy across 24 brain disorders, the technique outperforms current state-of-the-art systems.

3- Deepak V. K., S. R [9]

Brain abnormalities, notably tumors, pose a significant health risk, with cancer being the primary cause of mortality linked to these conditions. MRI is widely utilized for diagnosing and assessing brain tumors. As the number of acquired MRIs rises, computer-assisted diagnosis becomes imperative. However, traditional strategies in this realm have shown limited enhancements in performance. The paper introduces a Cat Swarm Optimization (CSO) algorithm-based CNN model for brain tumor classification in MRI images. This novel approach demonstrates outstanding performance, boasting 98% accuracy, precision, specificity, sensitivity,

ISSN NO: 2770-4491
Date of Publication:24-11-2023

and F-score. It surpasses other classification methods like support vector machines (SVM) and backpropagation neural networks (BPNN).

4- C. Narmatha, Sarah Mustafa Eljack [10].

The paper proposes a hybrid fuzzy brain-storm optimization algorithm for improved brain tumor MRI image classification, achieving a high accuracy of 93.85%. Additionally, a Cat Swarm Optimization (CSO) algorithm-based CNN model is introduced, demonstrating outstanding performance with 98% accuracy, surpassing other classification approaches. The paper also presents an effective method using optimized association rules for brain tumor MRI image classification, yielding around 90% accuracy.

5- P. Kanmani, P. Marikina [11].

a hybrid fuzzy brain-storm optimization algorithm for brain tumor MRI image classification, achieving impressive results with 93.85% accuracy, 94.77% precision, 95.77% sensitivity, and a 95.42% F1 score. Additionally, a Cat Swarm Optimization (CSO) algorithm-based CNN model is introduced, showcasing high performance with 98% accuracy, precision, specificity, sensitivity, and F-score, outperforming other classification approaches like support vector machines (SVM) and backpropagation neural networks (BPNN). The paper also presents an effective method using optimized association rules, yielding around 90% accuracy for brain tumor MRI image classification.

The algorithm for Proposed Classification

Disruption in cellular development and tissue expansion is the underlying cause of brain tumor formation. Magnetic Resonance Imaging (MRI), commonly known as MR images, plays a crucial role in classifying these tumors. MR imaging provides detailed and high-resolution images of the brain, enabling medical professionals to accurately identify and categorize different types of brain tumors. By analyzing the characteristics and patterns observed in these images, doctors can determine the tumor's location, size, shape, and extent. An essential aspect that MR images help assess is tissue expansion. Brain tumors often result in abnormal growth and expansion of tissues within the brain. By visualizing these changes through MR imaging, doctors can understand the degree to which the tumor has affected the surrounding tissues. Additionally, MR images are instrumental in detecting cell proliferation within brain tumors. Cell proliferation refers to the rapid division and multiplication of cells, which is a hallmark characteristic of cancerous growth. By examining MR images, radiologists can identify areas where cells are dividing abnormally. this paper using Construct the GLCM matrix by calculating the co-occurrence of gray-level values for pairs of pixels at specified spatial relationships. The spatial relationship can be defined in terms of pixel distance and direction. Typically, the GLCM is calculated for different pixel distances and directions to capture texture information at multiple scales and orientations then Normalization the GLCM matrix to eliminate any bias caused by differences in image size or intensity range. Common normalization methods include dividing each element of the GLCM by the total number of pixel pairs or by the sum of all elements in the GLCM. After that using Coot optimization for select features from GLCM matrix Depending on the specific application and desired characteristics, you can select a subset of relevant texture features from the extracted feature set. This step is often performed to reduce dimensionality and focus on the most discriminative features. After extracting the texture features using GLCM, you can utilize a Convolutional Neural Network (CNN) for classification. CNNs are a powerful class of deep learning models commonly used for image analysis tasks, including image classification. The proposed classification method follows a block diagram approach, as depicted in Figure 1.

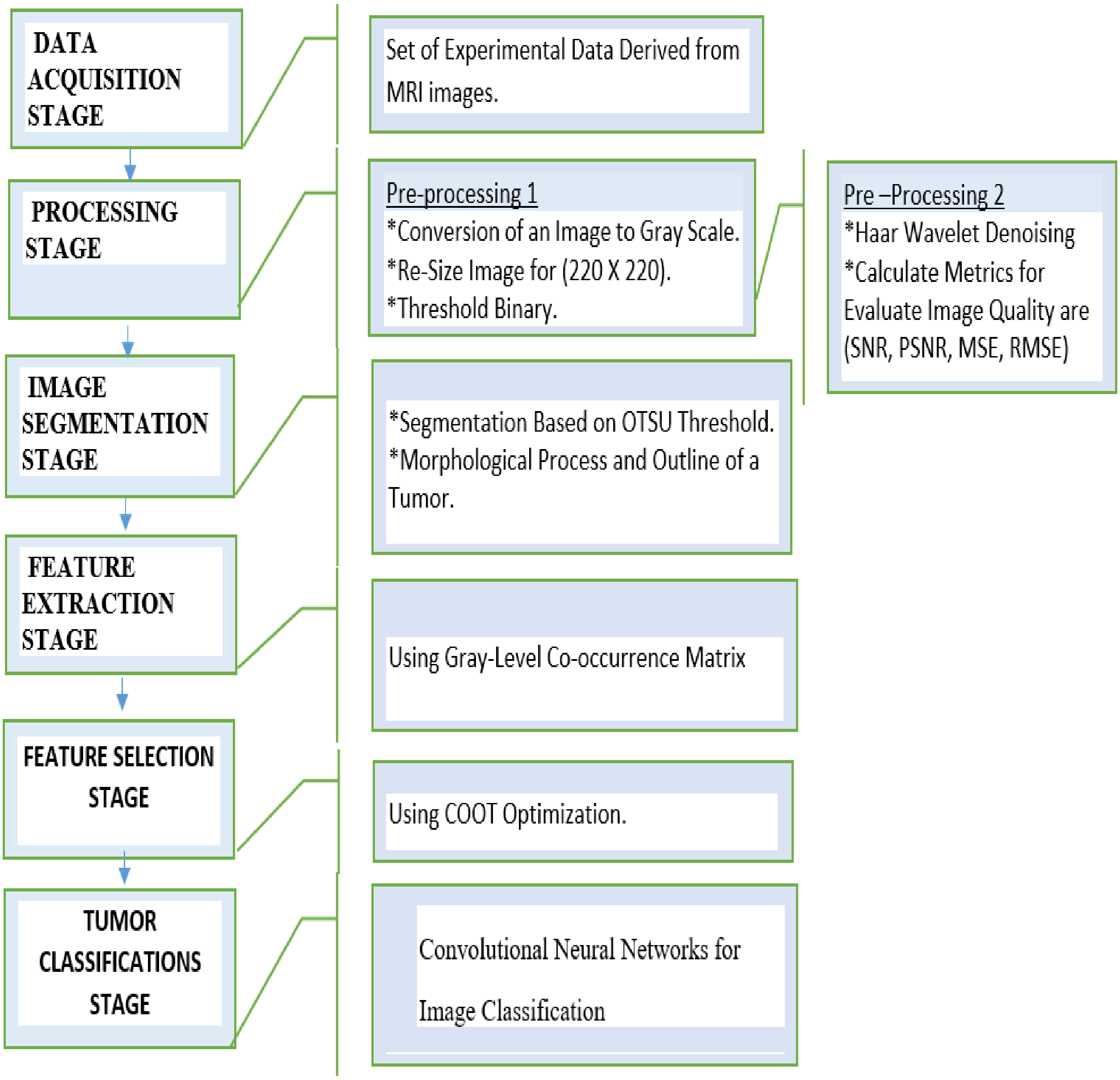


Fig. 1 illustrates the primary block diagram of the proposed classifier.

Data Acquisition

The dataset comprises a diverse collection of MRI images obtained from a wide range of individuals, including both males and females. It consists of 8,000 MR brain images, with 500 classified as normal and a7,500 as abnormal. These images were sourced from Kaggle. The normal images were selected from individuals who exhibited no signs of neurological disorders or brain abnormalities. Conversely, the abnormal images were collected from patients diagnosed with various conditions such as tumors, strokes, neurodegenerative diseases, and other brain abnormalities. Stringent quality control measures were employed during image acquisition to ensure dataset reliability and accuracy. Experienced radiologists carefully reviewed each image, adhering to established diagnostic criteria, to confirm its classification as either normal or abnormal. Additionally, all images underwent rigorous preprocessing steps to enhance image quality, eliminate artifacts and noise that might impact analysis. The dataset also includes pertinent clinical information for each patient, such as age, gender, medical history, and specific diagnosis. This additional information facilitates a comprehensive analysis of the correlation between brain abnormalities and various demographic or clinical factors. To simplify the analysis and processing of MRI scan images, the color images were converted to grayscale. This conversion retains only the intensity values, discarding color information. In the grayscale image, each pixel represents a specific intensity value. The intensity values range from 0 (black) to 255 (white), with different shades of gray representing varying levels of intensity.

ISSN NO: 2770-4491
Date of Publication:24-11-2023

To ensure consistency in display and enable easy comparison across scans, the MRI scan images were standardized to a size of 220x220 pixels. Factors such as display capabilities, storage requirements, and the level of detail needed for accurate analysis influenced the choice of this size. The acquisition process involves capturing MRI scan images using specialized equipment that utilizes magnetic fields and radio waves.

Pre-processing

The pre-processing stage involves converting the RGB image to grayscale. This conversion simplifies the image by representing it in shades of gray rather than color. It is often done because grayscale images require less computational resources and are sufficient for many analysis tasks. Additionally, reshaping the image may be necessary to ensure consistency in size and dimensions across different images. Reshaping can involve resizing or cropping the image to a specific resolution or aspect ratio required for further analysis or comparison. In this stage, wavelet transformation is commonly used for de-noising the image. Wavelet transforms decompose an image into different frequency components, allowing us to analyze and manipulate each component separately. By dividing the image into multiple levels of frequencies, including low and high frequencies, wavelet de-noising can effectively remove noise while preserving important details. The wavelet transform using in de-noising image for preprocessing MRI image, it is important to consider the specific requirements of the task. Wavelet transform is a powerful tool that can effectively reduce noise while preserving important features in an image. By applying wavelet transform, the image can be decomposed into different frequency bands. The high-frequency components usually contain noise and unnecessary details, while the low-frequency components represent the main structure and valuable information of the image. In order to remove noise without damaging the edges or affecting clarity and quality, a thresholding technique can be applied to the wavelet coefficients. This involves setting a threshold value below which coefficients are considered as noise and above which they are considered as signal. By selectively removing or attenuating coefficients below the threshold, noise can be effectively reduced while preserving important image features. By thresholding these coefficients, we can selectively remove or attenuate the noise while retaining important information related to anatomical structures or pathological features present in the MRI scan [12]. there are many types of wavelets in this paper using Haar wavelet since in pre-processing MRI images offers several advantages. Firstly, the Haar wavelet is a simple and computationally efficient transform that can be applied to decompose an image into its low-frequency and high-frequency components. This decomposition allows for the extraction of important features from the MRI image while reducing noise and irrelevant details. Secondly, the Haar wavelet has a unique property of being able to capture abrupt changes or edges in an image accurately. This property is particularly useful in MRI images as it helps in identifying boundaries between different tissues or structures within the brain or body. Figure 2 show shape image after pre-processing stage. Additionally, by applying the Haar wavelet transform, one can obtain a multi-resolution representation of the MRI image. This means that different levels of details can be extracted from the image, enabling better analysis and interpretation by medical professionals [13]. Table 1 show measures that calculated for some images in preprocessing.

ISSN NO: 2770-4491
Date of Publication:24-11-2023

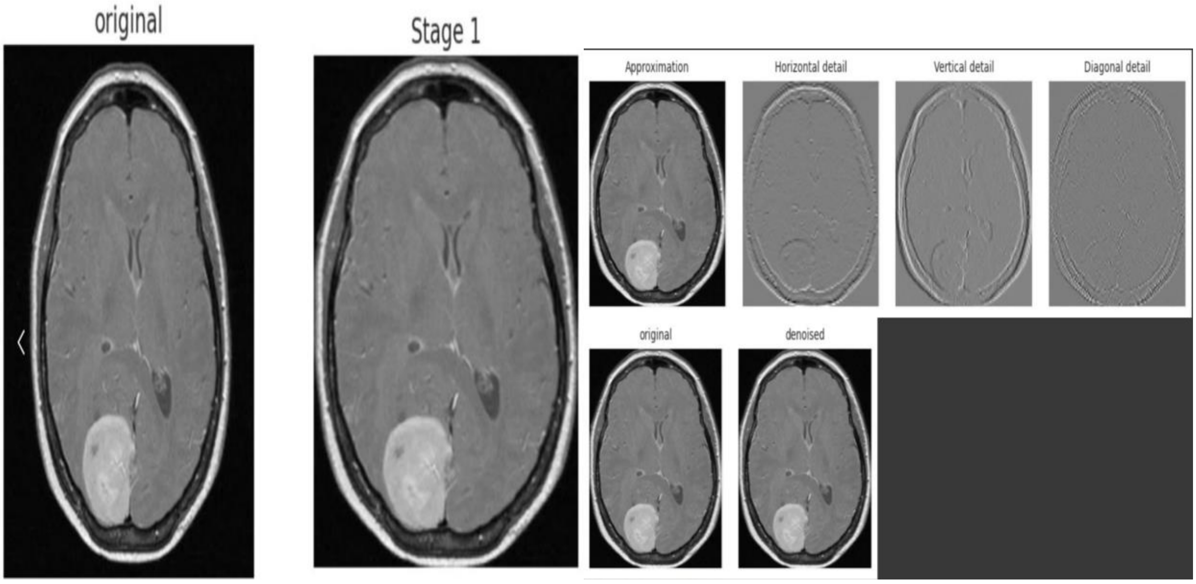
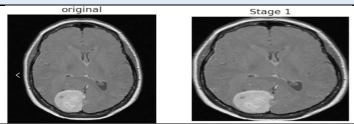
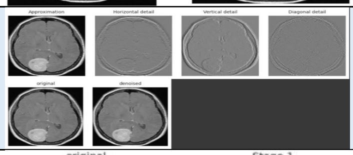
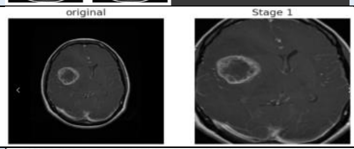
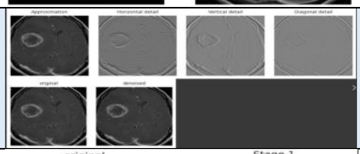
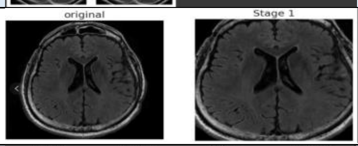
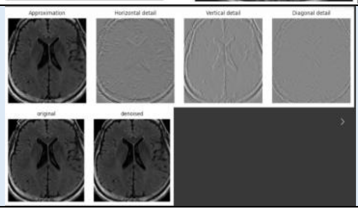


Figure 2: Denoised Image

TABLE 1
Measures of Denoising for Four Images

process	Images	PSNR	SNR	MSE	RMSE
De-noise 1 (meningioma)		11.53356	0.41151	4567.984	67.58687
De-noise 1.1		51.60846	22.22793	0.44898	0.67007
De-noise 1 (Glioma)		13.9300	3.72334	2630.7324	51.29066
De-noise 1.1		51.97743	24.30070	0.41241	0.642197
De-noise 1 (No-Tumor)		14.09783	1.07840	2531.0247	50.30929
De-noise 1.1		51.61906	23.57222	0.44789	0.66924

ISSN NO: 2770-4491
Date of Publication:24-11-2023

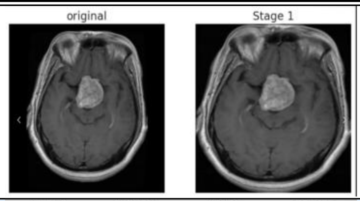
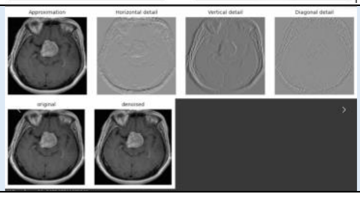
De-noise 1 (Pituitary)		11.77715	0.55001	4318.8165	65.717703
De-noise 1.1		51.84754	23.49561	0.42493	0.65187

Image Segmentation

A proper segmentation technique becomes crucial in order to accurately identify and differentiate between different image characteristics. The segmentation stage essentially involves separating the regions of interest from the background or other irrelevant areas within an image. The choice of segmentation method greatly impacts the accuracy and effectiveness of subsequent classification processes. Since there are various types of skins and textures, each with its own unique features, it becomes challenging to select a suitable segmentation approach that can effectively capture these diverse characteristics. Similarly, when dealing with lesions, there is a wide range of shapes, sizes, and colors that can vary significantly from case to case. Some lesions may have smooth transitions with the surrounding skin, making it difficult to precisely delineate their boundaries. On the other hand, certain lesions may exhibit irregular boundaries that further complicate the segmentation process. To address these challenges, researchers and practitioners in image analysis often employ advanced algorithms and techniques specifically designed for segmenting complex images [14] [15]. These algorithms were proposed to address the problem of accurately segmenting images. Each algorithm offers a unique approach and set of techniques to achieve this goal. Supervised classification techniques involve training a model using labeled data, where each image or pixel is assigned a specific class or category. The model then uses this training data to classify new, unlabeled images based on their features. This approach requires human intervention in the form manually labeling the training data, which can be time-consuming and subjective. Unsupervised classification techniques, on the other hand, do not require pre-labeled data. Instead, they analyze the inherent patterns and structures within the image to automatically group similar pixels or regions together. These algorithms use clustering methods such as k-means or hierarchical clustering to identify distinct classes within the image. Thresholding is a commonly used technique in image processing that involves converting a grayscale or color image into a binary image by selecting an appropriate threshold value [16]. OTSU thresholding is a widely used method, particularly in MRI image segmentation. It is an automatic thresholding technique that determines an optimal threshold value based on the image's histogram, separating objects or regions of interest from the background. In OTSU thresholding, the algorithm calculates the histogram of the MRI image, representing the distribution of pixel intensities. It then analyzes the histogram to find the optimal threshold value that maximizes the between-class variance. By comparing the variances between the foreground (object/region of interest) and background pixels at all possible thresholds, the algorithm selects the threshold value that yields the maximum between-class variance. The MRI image is then thresholder by assigning pixels below the threshold as background and pixels above the threshold as foreground. OTSU thresholding is advantageous as it automatically determines the optimal threshold without manual tuning or prior knowledge about the image. It is particularly useful for MRI images with varying intensity distributions or complex background structures. Post-processing steps like morphological operations or region-based methods can be applied to refine and improve the segmentation results after OTSU thresholding. Overall ,OTSU thresholding is a powerful technique in MRI segmentation, enabling automatic separation of foreground and background regions based on the image's histogram characteristics. It has wide applications in medical image analysis, including tumor segmentation, tissue classification, and lesion detection in MRI images [17].

Feature Extraction

ISSN NO: 2770-4491
Date of Publication:24-11-2023

This information extraction process involves analyzing the spatial arrangement and distribution of pixel intensities within an image. By examining the patterns, shapes, and variations in texture, statistical textural analysis can reveal important insights about the underlying tissue composition. One key advantage of texture analysis is its ability to differentiate between natural and irregular tissues. These textural characteristics were derived by applying the Gray Level Co-occurrence Matrix (GLCM) analysis to the LL sub bands obtained from the Wavelet Transform (WT) decomposition. The GLCM is a statistical method that measures the spatial relationships between pixels in an image. By analyzing the GLCM components of the LL sub bands, various textural features were extracted. By reducing the data representation pattern, extracting features becomes a crucial step in various machine learning tasks. This process involves extracting and transforming the intricate details of input data into a concise and meaningful representation known as a feature vector. A feature vector is essentially a numerical representation that captures the relevant characteristics or attributes of the input data. These features are carefully selected to highlight important patterns or properties that can aid in solving specific problems. This paper used a hybrid method (Haar WT + GLCM) table2 show features that extracted from matrix GLCM. Classification is improved by selecting a suitable set of characteristics [18-19]. The following matrices' properties were also gleaned: dissimilarity, contrast, ASM, energy, correlation, homogeneity, mean, standard deviation, entropy, RMS, variance, kurtosis, and skew, ASM.

TABLE 2
Feature extracted by (HWT+GLCM) to 5 images

feature	image 1	image 2	image 3	image 4
Contrast	16.19551	29.69178	126.86488	2426.62826
Correlation	0.695506	0.816206	0.958054	0.755336
Energy	0.739005	0.9081044	0.97653	0.830831
Homogeneity	13.49626	37.78953	156.55666	2908.44489
Mean	0.12117	0.632231	11.03243	32.201652
standard deviation	5.55748	12.68145	51.880217	84.70227
Entropy	0.033762	0.123551	1.130481	3.171552
RMS	0.02179	0.049792	0.2080011	0.35536
Variance	30.88562	160.81929	2691.557005	7174.475038
Kurtosis	2102.3483	401.35581	21.51887	6.063380
Skewness	45.84046	20.00839	4.48986	2.25019
Dissimilarity	18.98104	59.65471	227.7725	3510.13792
ASM	27.11578	46.09682	225.06098	3605.04316

Feature Selection

By reducing the data representation pattern, extracting features becomes a crucial step in various machine learning tasks. This process involves extracting and transforming the intricate details of input data into a concise and meaningful representation known as a feature vector. A feature vector is essentially a numerical representation that captures the relevant characteristics or attributes of the input data. These features are carefully selected to highlight important patterns or properties that can aid in solving specific problems. However, treating feature selection solely as a combinatorial optimization problem may overlook certain important aspects. While maximizing feature space separability is crucial for achieving accurate classification, it is equally important to consider the interpretability and generalizability of the selected features. In many real-world scenarios, having a high classification accuracy alone may not be sufficient if the selected features are not easily interpretable or do not generalize well to unseen data. Therefore, researchers have started incorporating additional criteria into the objective function of feature selection algorithms. One such criterion is the sparsity of the selected features. Sparse feature selection aims to identify a small subset of relevant features that can effectively represent the underlying data distribution. By promoting sparsity, we can achieve a more interpretable model that focuses on the most discriminative attributes while discarding irrelevant or redundant ones. By reducing the dimensionality of the feature space, feature selection aims to eliminate irrelevant or redundant features that may not contribute significantly to the accuracy of a classification method. This process helps in simplifying the model and improving its efficiency by focusing only on the most informative features. Feature selection also plays a crucial role in enhancing the anticipated accuracy of a classification method. By selecting relevant features, it allows the model to focus on capturing the most discriminative patterns and relationships within the data. This can lead to better generalization and improved predictive performance, as the model is less likely to be influenced by noise or irrelevant information. Furthermore, feature selection aids in improving visualization and comprehension of induced concepts. When dealing with high-dimensional data, it becomes challenging to interpret and understand the underlying patterns or relationships. By selecting a subset of relevant features, it becomes easier to visualize and comprehend these concepts, as they are represented in a lower-dimensional space that is more easily interpretable by humans. In this paper, we propose the utilization of coot optimization for feature selection. Feature selection plays a crucial role in various domains such as machine learning, data mining, and pattern recognition. It involves identifying the most relevant features from a given dataset that contribute significantly to the prediction or classification task at hand. Coot optimization is a metaheuristic algorithm inspired by the behavior of cooperative coots in nature. These birds exhibit collective decision-making abilities while foraging for food, where they optimize their search patterns to maximize their overall efficiency. Similarly, coot optimization mimics this behavior by iteratively selecting and evaluating subsets of features to find an optimal solution. The main advantage of using coot optimization for feature selection is its ability to handle high-dimensional datasets effectively. Traditional methods often struggle with large feature spaces due to increased computational complexity and overfitting issues. Coot optimization tackles these challenges by intelligently exploring the search space and identifying subsets of features that collectively provide the best performance [20-21]. table 3 show the features that select by COOT optimization from GLCM.

TABLE 3
Feature Selection by (COOT) to 5 images

feature	image 1	image 2	image 3	image 4
energy	0.739005	0.9081044	0.97653	0.830831
homogeneity	13.49626	37.78953	156.55666	2908.44489
mean	0.12117	0.632231	11.03243	32.201652
entropy	0.033762	0.123551	1.130481	3.171552
RMS	0.02179	0.049792	0.2080011	0.35536
kurtosis	2102.3483	401.35581	21.51887	6.063380
skewness	45.84046	20.00839	4.48986	2.25019

Tumor Classification

ISSN NO: 2770-4491
Date of Publication:24-11-2023

Convolutional Neural Networks (CNNs) are highly effective in the classification of tumor MRI images, showcasing their success in various image recognition tasks, including medical image analysis. To classify tumors in MRI images using CNNs, the following steps can be followed. First, organize a dataset of MRI images containing tumor and non-tumor (normal) samples, ensuring each image is labeled accordingly. Augmenting the dataset by applying techniques like rotation, scaling, or flipping can enhance the model's generalization. Design the CNN architecture, which typically includes convolutional layers, pooling layers for down sampling, and fully connected layers for classification. Established architectures like VGGNet, ResNet, or Inception can be used, or a custom architecture can be designed based on the task's complexity. Preprocess the MRI images by resizing them to a consistent size, normalizing pixel values, and applying enhancements or noise reduction techniques as required. Train the CNN using the labeled MRI images, enabling the model to learn relevant features and map them to the tumor or non-tumor classes through forward and backward propagation, along with optimization. Evaluate the trained CNN model using a separate validation set, utilizing metrics such as accuracy, precision, recall, F1 score, and ROC curve to assess its performance. Test the model on an independent set of MRI images that were not used during training or validation. This step helps estimate the model's ability to generalize and accurately classify unseen tumor images. Optionally, fine-tune the CNN by adjusting its architecture, hyper parameters, or incorporating additional training data to further enhance the classification performance. CNNs excel in tumor classification due to their capability to automatically learn relevant features from MRI images. The hierarchical structure of CNNs enables them to capture intricate patterns and textures indicative of tumor presence. Training CNNs on diverse datasets aids in distinguishing between tumor and non-tumor images, thereby assisting in the diagnosis and treatment of patients. It is important to note that the success of CNNs in tumor classification relies on the quality and diversity of the dataset, as well as accurate expert annotations. Regular evaluation, validation, and fine-tuning of the model are crucial for achieving optimal results in tumor classification using CNNs [22-23].

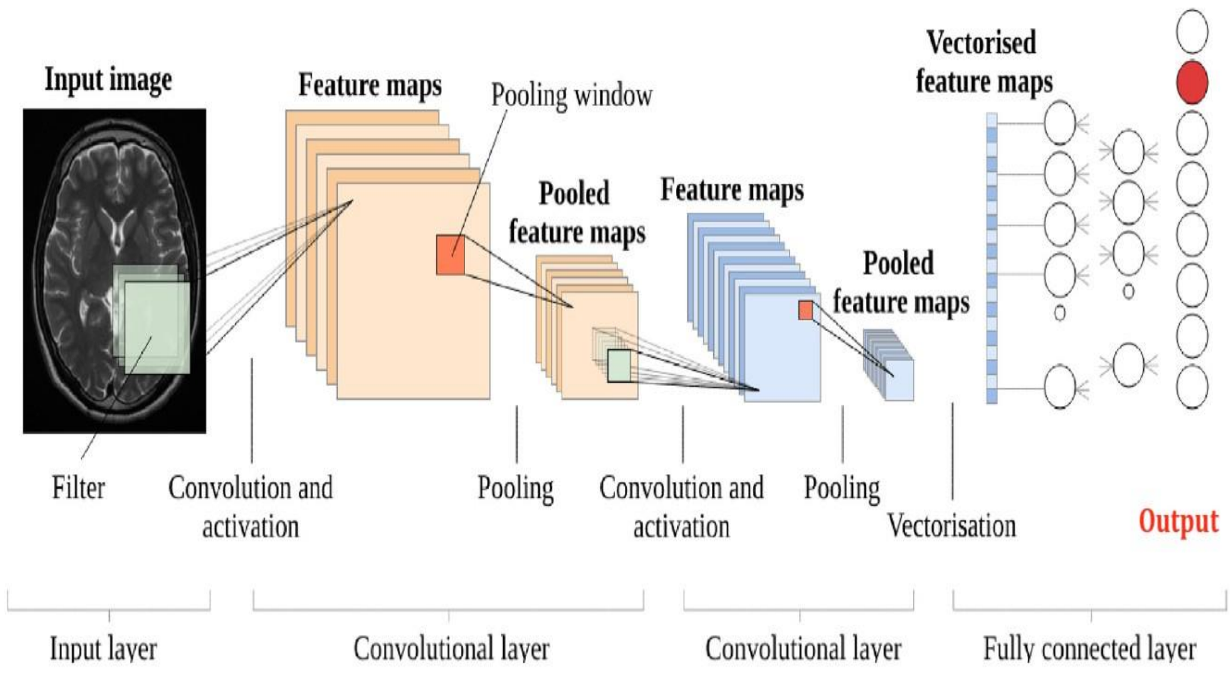


Figure 3: Building a Convolutional Neural Network (CNN) for Image Classification

ISSN NO: 2770-4491
Date of Publication:24-11-2023

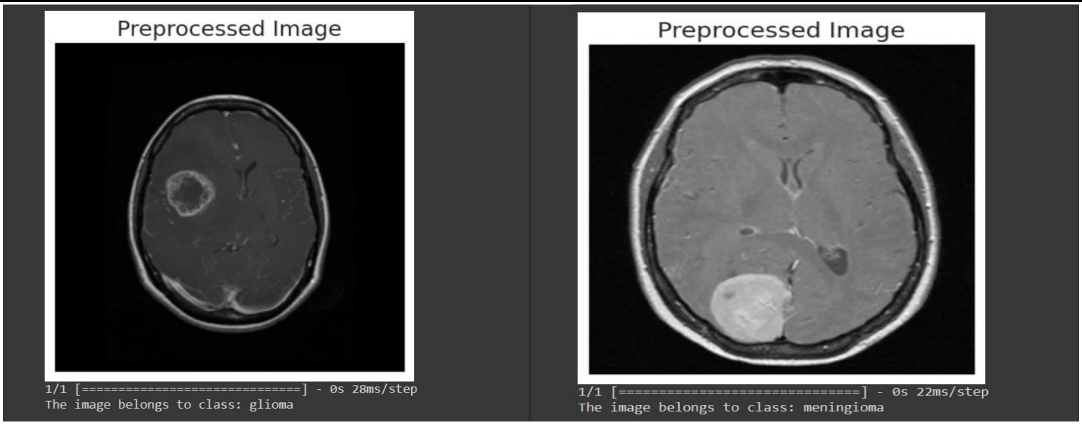


Figure 4: True Predicted Classification of MRI Images

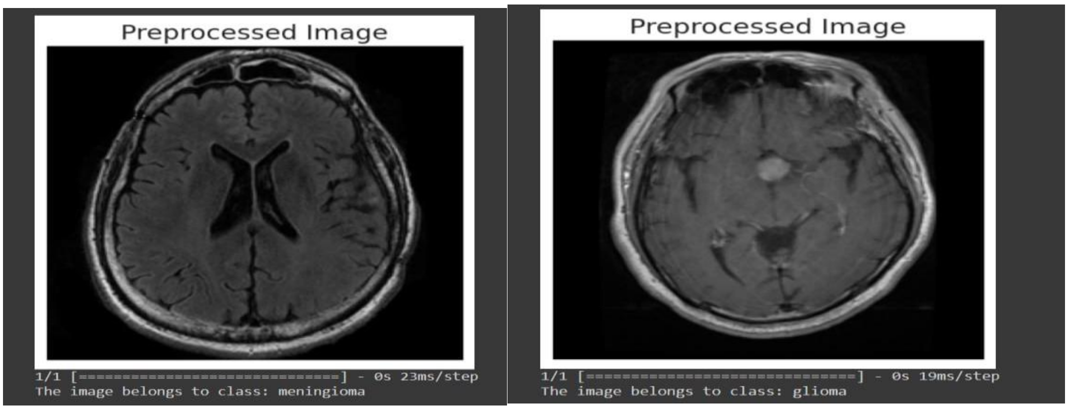


Figure 5: False Predicted Classification of MRI Images

Building and Training a Deep Learning Model for Image Classification Steps:

- Import the necessary libraries: keras and Sequential from keras. models.
- Create a sequential model object and define the architecture using Conv2D, MaxPooling2D, Flatten, and Dense layers.
- Compile the model with the desired optimizer and loss function.
- Train the model using the fit () method with the training data.
- Evaluate the model's performance on the test data using the evaluate () method.
- Save the trained model.
- Plot the training history using the history object.
- Import the necessary libraries: Image from PIL and tensor flow.
- Load and preprocess the image: resize, convert to NumPy array, perform additional preprocessing steps, and add a batch dimension.
- Make predictions on the preprocessed image using the trained model.
- Retrieve the predicted class index and map it to the corresponding class name.
- Print the predicted class name.

Results

Table 4 presents the results of the experiments conducted using the depicted workflow for the segmented outcome and the extracted tumor region. Figure 6 showcases the training network for the CNN (Convolution Neural Network). Lastly, Figure 7 show Accuracy and Failure Rates during Training and Testing Phase. Figure 8 show final result of run our work.

ISSN NO: 2770-4491
Date of Publication:24-11-2023

Table 4: Segmentation of MRI Images

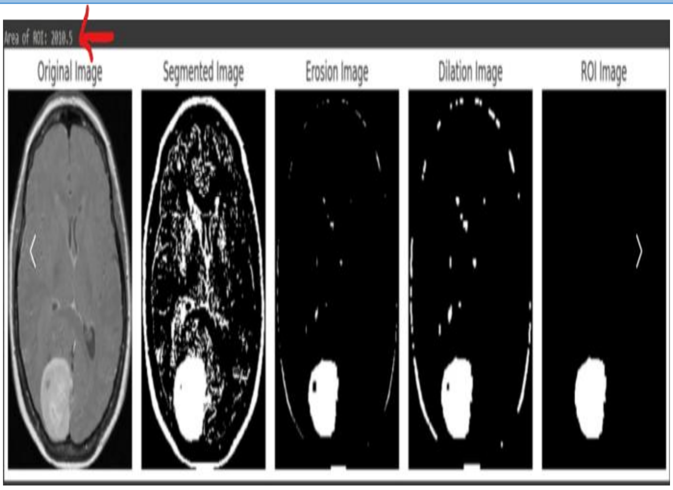
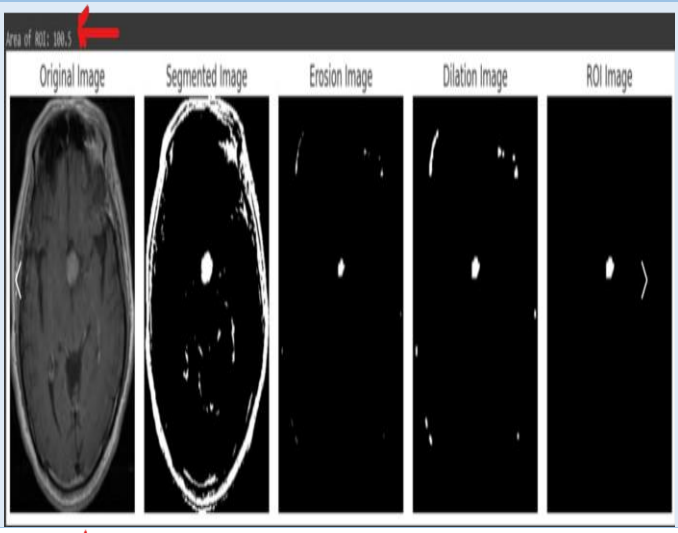
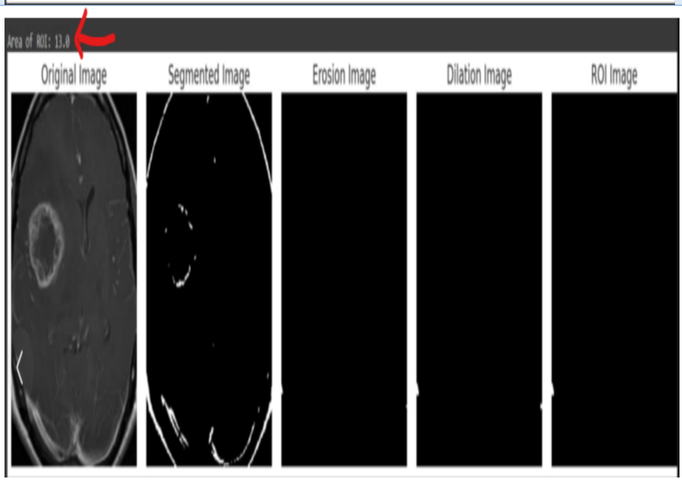
Images	Segmented outcome	Tumor region
Meningioma image		2010.5
Pituitary image		100.5
Glioma image		870.0

Figure 6: The performance of the network

Figure 7: Accuracy and Failure Rates during Training and Testing Phase

ISSN NO: 2770-4491
Date of Publication:24-11-2023

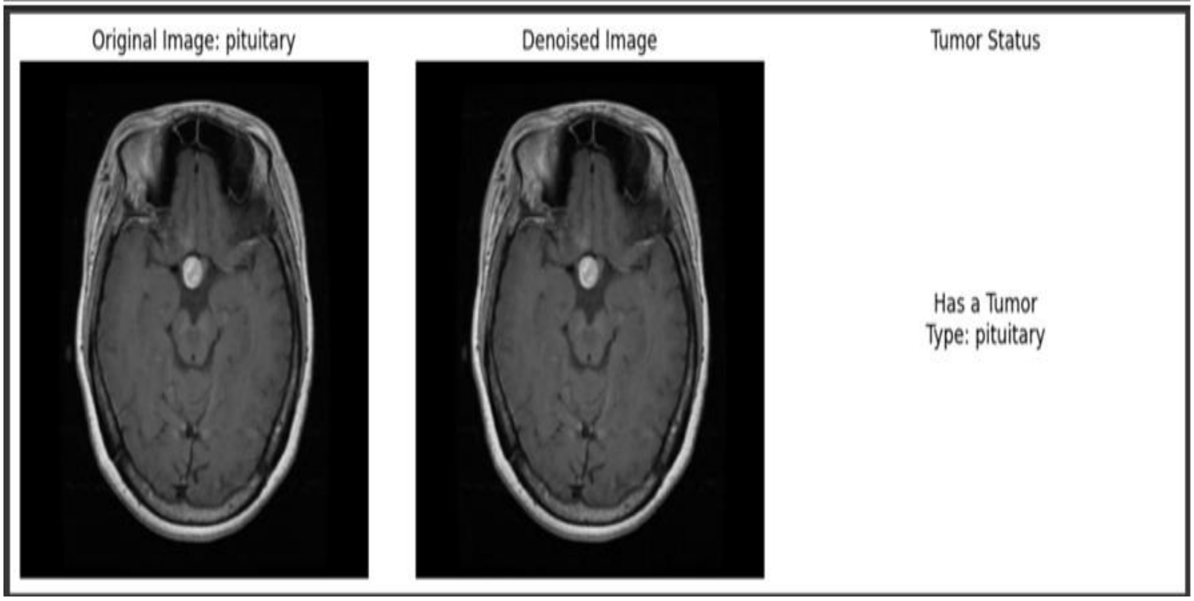


Figure 8: Carrying out our work

Conclusion

Automated Brain Tumor Detection in MRI Images using Haar Wavelet Transform, COOT, and CNN In this study, an automated approach was developed for the detection of brain tumors in MRI images. The research utilized a total of 8,000 images, with 6,689 images used for training and 1,311 images used for testing. The approach integrated the use of Haar wavelet transform (HWT), Cascaded Object-Oriented Trackers (COOT), and Convolutional Neural Networks (CNN) to achieve accurate and efficient tumor detection. The approach consisted of two main phases. In the first phase, the HWT technique was applied for pre-processing and feature extraction. This involved analyzing the statistical characteristics of the MRI images and extracting relevant features using the Haar wavelet transform. Additionally, Gray Level Co-occurrence Matrix (GLCM) features were computed to capture the texture information within the images. In the second phase, COOT was utilized to select the most optimal features for tumor classification. COOT allowed for the identification and extraction of discriminative features from the pre-processed images, enhancing the overall accuracy of the classification process. Subsequently, a CNN with supervised learning was employed for image classification, specifically targeting the distinction between benign and malignant tumors. The CNN model was trained using 6,689 images and evaluated on the remaining 1,311 test images. The results of the proposed approach demonstrated exceptional accuracy in tumor detection and classification, with an impressive accuracy rate of 99.94% and minimal loss. These findings highlight the effectiveness and reliability of the integrated Haar wavelet transform, COOT, and CNN approach in accurately detecting and classifying brain tumors in MRI images, based on the large dataset of 8,000 images.

References

1. Aparna, Vyas., Soohwan, Yu., Joonki, Paik. (2018). Wavelets and Wavelet Transform. doi: 10.1007/978-981-10-7272-7_3.
2. Vladislav, Skorpil., Jiri, Stastny. (2003). Wavelet transform for image analysis. doi: 10.1109/SIBCON.2003.1335720.
3. Viresh, Ratnakar. (2001). Wavelet transform coding technique.
4. Shuang, Zhang., Jinru, Wu., Enze, Shi., Sigang, Yu., Yongfeng, Gao., Lihong, Li., Marc, J., Pomeroy., Zhengrong, Jerome, Liang. (2023). MM-GLCM-CNN: A multi-scale and multi-level based GLCM-CNN for polyp classification.. Computerized Medical Imaging and Graphics, doi: 10.1016/j.compmedimag.2023.102257 .
5. pallavi, Malavath., Nagaraju, Devarakonda. (2022). Coot optimization based Enhanced Global Pyramid Network for 3D hand pose estimation. doi: 10.1088/2632-2153/ac9fa5.

ISSN NO: 2770-4491
Date of Publication:24-11-2023

6. Hu, Hui., Kang, Wenxiong., Deng, Feiqi. (2017). CNN model, CNN training method and vein identification method based on CNN.
7. Osman, Özkaraca., Okan, İhsan, Bağrıaçık., Hüseyin, Gürüler., Faheem, Khan., Jamil, Hussain., Jawad, Khan., Umm-e, Laila. (2023). Multiple Brain Tumor Classification with Dense CNN Architecture Using Brain MRI Images. Reproductive and developmental Biology, doi: 10.3390/life13020349 .
8. Muhammad, Hameed, Siddiqi., Mohammad, Azad., Yousef, Alhwaiti. (2022). An Enhanced Machine Learning Approach for Brain MRI Classification. Diagnostics, doi: 10.3390/diagnostics12112791.
9. Deepak, V., K.., S., R. (2022). Classification of brain tumours in MRI images using convolutional neural network through Cat Swarm Optimization. Expert Systems, doi: 10.1111/exsy.13021.
10. C., Narmatha., Sarah, Mustafa, Eljack., Afaf, Abdul, Rahman, Mohammed, Tuka., S., Manimurugan., Mohammed, Mustafa. (2020). A hybrid fuzzy brain-storm optimization algorithm for the classification of brain tumor MRI images. Journal of Ambient Intelligence and Humanized Computing, doi: 10.1007/S12652-020-02470-5.
11. P., Kanmani., P., Marikkannu. (2018). MRI Brain Images Classification: A Multi-Level Threshold Based Region Optimization Technique. Journal of Medical Systems, doi: 10.1007/S10916-018-0915-8.
12. Katran, L. F. (2019). Hybrid method for the detection of brain tumor image usingimproving K-Mean and hybrid multilevel image fusion. http://mail.jardcs.org/abstract.php?id=94.
13. Indrarini, Dyah, Irawati., Sugondo, Hadiyoso., Yuli, Sun, Hariyani. (2020). Multi-wavelet level comparison on compressive sensing for MRI image reconstruction. Bulletin of Electrical Engineering and Informatics, doi: 10.11591/EEI.V9I4.2347.
14. Alaa, Tom., Jihad, S., Daba. (2023). Revisited Otsu Algorithm for Skin Cancer Segmentation. WSEAS transactions on information science and applications, doi: 10.37394/23209.2023.20.7.
15. Adeyinka, Tella. (2022). Improved Otsu Algorithm for Segmentation of Malaria Parasite Images. doi: 10.1002/9781119819165.ch10.
16. Afreen, Shaikh., Sharmila, Botcha., M., Hari, Krishna. (2022). Otsu based Differential Evolution Method for Image Segmentation. arXiv.org, doi: 10.48550/arXiv.2210.10005.
17. Gang, Liu., ZhiFeng, Zhang., Xiao, Cui., Jinhui, Kuang., J., Cai., Xiaohui, Ji. (2022). Chromosome Image Segmentation Based on OTSU and Region Growing Algorithm. doi: 10.1109/PRAI55851.2022.9904165.
18. Edi, Faisal., Agung, Nugroho., Ruri, Suko, Basuki., Suharnawi, Suharnawi. (2022). GLCM Based Locally Feature Extraction On Natural Image. JAIS (Journal of Applied Intelligent System), doi: 10.33633/jais.v7i2.6569.
19. Aya, Alsalihi., Hadeel, K., Aljobouri., Enam, K, Altameemi. (2022). GLCM and CNN Deep Learning Model for Improved MRI Breast Tumors Detection. International Journal of Online Engineering (ijoe), doi: 10.3991/ijoe.v18i12.31897.
20. Mahmoud, H., El-Bahay., Mohammed, Elsayed, Lotfy., Mohamed, Abd, Elhameed. (2023). Effective participation of wind turbines in frequency control of a two-area power system using coot optimization. Protection and Control of Modern Power Systems, doi: 10.1186/s41601-023-00289-8.
21. Archita, Goyal., D., K., Srivastava. (2023). Optimization of helical soil nailing behaviors by response surface methodology and hybrid Coot optimization. International Journal for Numerical and Analytical Methods in Geomechanics, doi: 10.1002/nag.3533.
22. Sher, Shermin, Azmiri, Khan., A., ProvÃ., Uzzal, Kumar, Acharjee. (2023). MRI-based Brain Tumor Image Classification Using CNN. Asian Journal of Research in Computer Science, doi: 10.9734/ajrcos/2023/v15i1310.
23. Jhan, Yahya, Rbat., Hadeel, K., Aljobouri., Ali, M., Hasan. (2022). MRI brain tumor classification using robust Convolutional Neural Network CNN approach. doi: 10.1109/IICCIT55816.2022.10009913.