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Fusion based Image Enhancement Approach for Brain Tumor Detection

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Abstract— Magnetic Resonance Imaging (MRI), is a crucial technology used in the processing of medical images that provides insights into the anatomy of soft organs in the human body and helps in detecting brain tumors and spinal tumors. Despite advances in technology, most images have intrinsic drawbacks such as reduced contrast and brightness, and noise. Several contrast enhancement techniques are used such as, HE, BBHE, DSIHE, CLAHE, RMSHE, and their fusion, have been deployed on different MRI images to handle these problems. Metrics such as, entropy, PIQE and BRISQUE are used in the assessment of the results. Through the different fusion combinations, most prominent results are obtained from CLAHE-RMSHE fusion with an entropy value of 6.2516 and BRISQUE value of 40.14.

Keywords-RMSHE, BBHE, BRISQUE, CLAHE, Fusion, DSIHE

I. Introduction

Brain images, in particular MRI scans, often suffer due to poor brightness, poor contrast, and the presence of unwanted noise [14]. MRI scans are used to identify abnormal tissue growths in the brain. Abnormal development of cells in the brain leads to the formation of tumors, which can be classified as primary or secondary. If found, the growth should be identified and removed. Typical signs of a brain tumor include migraines, nausea, blurred vision, disorientation, and weakness in the limbs. Brain tumor can be treated by surgery, radiation therapy and chemotherapy.

Tumor detection in MRI images is difficult due to dark images, limited discrimination, and noise interference [1, 20]. Various contrast enhancement techniques like HE, BBHE, CLAHE, RMSHE and DSIHE are under investigation to improve the accurate detection of brain tumors. [16] Contrast enhancement techniques improve the visibility of objects in an image by increasing the relative brightness.

The fusion of contrast enhancement techniques has been proposed as a means of improving brain tumor detection by making medical images more useful for accurate diagnosis in the medical field [18].

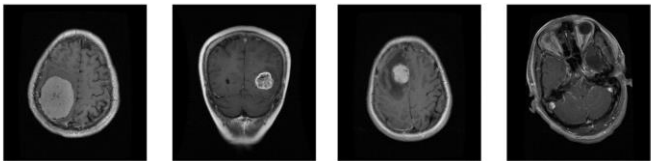

Figure. 1. Brain MRI Images [21,22]

A few samples of MRI brain images are shown in Figure 1 above.

A fusion of contrast-enhancing techniques has been proposed as a means of improving brain tumor detection by upgrading medical images to the best standard for practically accurate medical diagnosis. [15] The term fusion generally refers to a strategy for extracting knowledge obtained from multiple disciplines. The goal of image fusion is to combine the data from multiple images captured of the same scene into a single image while preserving the important and significant characteristics of the individual source images. Researchers studied the center weighted median (CWM) filter, a type of weighted median filter that places more weight on the mean of each frame. [17] This filter can reduce the effects of additive white noise and impulsive noise while preserving important image characteristics. The resulting combined image is more informative and complete than any of the input photos, making it suitable for human vision and computer perception.

The remaining part of the document is structured in the following manner: Section II examines previous research, current approaches, and available methods. Additionally, in Section III, present an outline of the proposed approach. The outcomes of proposed techniques are discussed in Section IV. Lastly, Section V concludes the present study and offers some insights into potential future improvements.
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II. RELATED WORKS

Numerous researchers have already conducted a substantial amount of research in this field. This section provides a summary of the previously conducted research work.

A. Histogram Equalization (HE)

A study by Hardeep Kaur and Jyoti Rani used various HE techniques to improve MRI images of brain tumors [3]. Due to the low contrast, the histogram of his MRI image of the brain is undispersed and tapers only to the left. To solve this problem, HE is applied to improve the image contrast and create a uniformly distributed histogram. HE techniques, despite their effectiveness, cannot provide insight into spatial relationships between pixels.

The HE process can be described by the following equation:

$$P_n = \frac{no.of\ pixel\ with\ intensity\ n_k}{total\ no.of\ pixels\ n}$$

$$n = [0, i-1]$$

The gray level values of the input image are represented by [0,…,i-1] in the formula (1).

B. Contrast Limited Adaptive Histogram Equalization (CLAHE)

In research papers [8], both AHE and CLAHE have been used to increase the contrast of MRI images. The AHE method is used to enhance features in images where the contrast needs to be improved. The AHE method differs from the simple HE approach in that it computes multiple histograms related to certain regions of the image and uses them to restore the image to its original luminance values. This method of enhancing local contrast improves image quality and makes it more suitable to anticipate.

CLAHE is an improved version of Adaptive HE. CLAHE solves the problem of extra noise enhancement and overexposure of bright areas that can occur with the AHE approach. CLAHE manages image contrast by controlling the contrast enhancement of adjacent pixels, resulting in a transfer function that reduces the problem of noise enhancement.

C. Dualistic Sub Image Histogram Equalization (DSIHE)

Wang et al [9] initially introduced the concept of DSIHE. A type of BBHE that sorts images into groups based on median values is called DSIHE. A method has been proposed to enhance and segment medical images based on DSIHE [7]. As described in [13], the proposed algorithm includes the following series of steps:

1. Generate a histogram from the input image.
2. Calculate the median value (M) of the histogram.
3. Partition the histogram into two parts considering the median value (M).
4. Apply techniques such as cumulative distributions and probability distributions to perform histogram equalization for both partitions.

Assuming that a grayscale threshold is used to divide image X into two sub-images, XA and XB, then,

$$X = X_A + X_B \qquad (2)$$

results. In this,

$$X_A = \left(X_{(i,j)} \middle| X_{(i,j)} < X_{e'} \,\forall X_{(i,j)} \in X\right) \qquad (3)$$

$$X_B = \left(X_{(i,j)} \middle| X_{(i,j)} < X_{e,} \;\forall X_{(i,j)} \in X\right) \qquad (4)$$

Here, X_A is constructed from $\{X_0, …, X_{e-1}\}$ and X_B is constructed from $\{X_e, …, X_{r-1}\}$

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D. Recursive Mean Separate Histogram Equalization (RMSHE)

According to [6], RMSHE, which is an extension of BBHE, offers adjustable brightness preservation and enhances contrast for that purpose. It has been found to enhance images naturally and more effectively.

The paper [11] describes RMSHE as applying the BBHE algorithm recursively. Simply put, RMSHE runs the BBHE algorithm recursively. The input grayscale image is split into '2n' sub-histograms, and then these individual sub-histograms are adjusted separately using a criterion named 'n' according to the method described. The brightness of the final image, or the computed average, rises and is equal to the input brightness value as RMSHE makes sure that the scaled brightness is retained. The degree of luminance preservation that RMSHE can achieve is directly proportional to the value of n, which corresponds to the number of times the recursive process is performed. As the value of n increases, the brightness preservation of the enhanced image improves.

$$E(Y) = \left[\frac{XG - X_m}{2^n}\right] \quad (5)$$

According to [11], equation (5) defines the output image brightness E(Y). where XG represents the average gray level and X_m represents the average efficiency.

Some studies suggest that weighted and recursively separated HE can preserve brightness while improving the contrast. Unlike BBHE, which performs mean-based histogram segmentation only once, RMSHE performs it recursively multiple times. [5]

E. Brightness Preserving Bi-Histogram Equalization (BBHE)

A comparative study by K. Akilaa, L.S. Jayashreeb and A. Vasuvic [10] aims to compare several HE techniques to determine suitable algorithms for image enhancement and subsequent processing. BBHE is used in the research study based on a specific formula, as the conventional HE technique can change the brightness of the image significantly.

BBHE can improve image noise reduction and avoid blurring image details. It can improve enhancement performance on applying an edge-preserving filter. Here, let X_m be the average of the input image, and x_l and x_u denote the two sublevels of the input image. The output of BBHE can be expressed as:

$$Y = f_L\,(x_l) \cup f_u\,(x_u) \quad (6)$$

The resultant image Y is obtained by combining the two separate halves, xl and xu, as shown in equation (6).

The proposed methodology is further elaborated in the following section.

III. PROPOSED METHOD

The proposed model can be divided into two primary elements, as shown in Figure 2. The initial component involves the processing of the MRI image using various techniques such as RMSHE, BBHE, CLAHE, and DSIHE. These methods are combined in different ways to create fusion combinations. The second component involves the evaluation of the model using parameterized methods

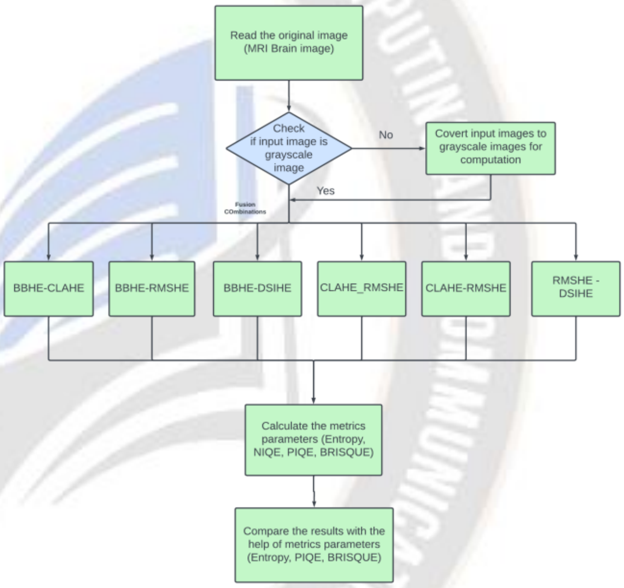

Figure. 2. Process for the suggested technique

BBHE-CLAHE Fusion: BBHE and CLAHE can be combined to produce a fused image that leverages the strengths of both techniques. This method applies CLAHE to the high contrast sections of the image while BBHE is applied to the low contrast regions of the image. The final outcome is achieved by merging these regions together. by taking their weighted average for which 0.5 value is taken for BBHE and 0.5 value is taken for CLAHE. The resulting fused image has improved overall contrast and brightness while avoiding the noise amplification that can occur with CLAHE alone.

BBHE - RMSHE Fusion: When BBHE and RMSHE are combined, their respective strengths can be leveraged to produce an even better output image. This fusion technique involves equalizing the histogram of the image using both

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BBHE and RMSHE, and then merging the resulting images using a weighted average for which 0.5 value is taken for BBHE and 0.5 value is taken for RMSHE. By using both techniques, the brightness preservation and contrast enhancement can be further improved, resulting in a more visually appealing image.

BBHE – DSIHE Fusion: Fusing BBHE and DSIHE involves applying both techniques to the input image and then combining their outputs to obtain the final enhanced image. The idea is to leverage the strengths of both techniques while minimizing their weaknesses. BBHE helps preserve image brightness while increasing contrast, while DSIHE manages local contrast variations and can adapt to content in different regions of the image. The resultant image is obtained by combining them by taking their weighted average for which 0.5 value is taken for BBHE and 0.5 value for DSIHE. After combining them, it is possible to achieve an enhanced image that has better overall contrast and brightness while preserving local details.

CLAHE – RMSHE Fusion: By fusing these two methods, can take advantage of the strengths of both techniques. CLAHE can preserve local details and prevent over-enhancement, while RMSHE can provide a more natural-looking enhancement and better brightness preservation. The resultant image is obtained by combining them by taking their weighted average for which 0.5 value is taken for CLAHE and 0.5 value for RMSHE. The resulting image has improved contrast and better brightness preservation while preserving important details in the image.

RMSHE – DSIHE Fusion: The fusion of these two techniques involves using the recursive approach of RMSHE to further enhance the dualistic sub-image approach of DSIHE. In this fusion technique, the input image is first subjected to DSIHE, which separates the image into a number of sub-images and equalizes their histograms separately. Then, the RMSHE technique is applied recursively to each of these sub-images to further enhance their contrast.

The advantage of combining these two techniques is that DSIHE is good at preserving local contrast in the image, while RMSHE is good at maintaining the brightness of the image while enhancing its contrast. The resultant image is obtained by combining them by taking their weighted average for which 0.5 value is taken for RMSHE and 0.5 value for DSIHE. The fusion of these techniques results in an image that has both good local contrast and overall brightness preservation, making it visually appealing and useful for various image processing applications.

Once the MRI image is analyzed, the model uses an external library to convert the input image to grayscale. These grayscale images are used in the computation, where the output images from two different methods are combined using a weighted average approach. The resulting image is obtained by combining various histogram equalization techniques. The obtained values are then used to calculate various metric entities such as entropy, PIQE, NIQE, BRISQUE. Therefore, the numerical value of the metric parameter is used to compare images

IV. RESULTS AND DISCUSSIONS

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A. Subjective Evaluation

A visual analysis of the proposed algorithm has been performed by analyzing image quality using human vision [19]. Using medical MRI scans from established databases, the applicability and effectiveness of the proposed method are evaluated in contrast to other existing methods

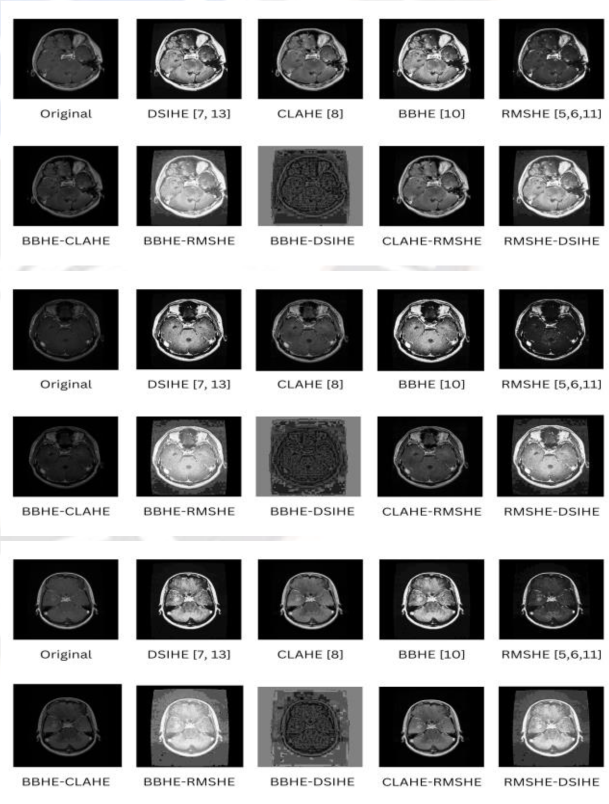

Figure 3. Subjective Results. The images above display the outcomes of applying several algorithms to three representative images from the dataset. [27,28]

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B. Objective evaluation

In this study, several objective evaluation parameters are used to check the performance of the proposed approach relative to other existing methods. [19]

Entropy: The amount of unpredictability that exists between pixels of the same intensity is indicated by an image's entropy value. In other words, entropy indicates how crowded the pixels in an image are. Evenly distributed pixels increase the entropy value.

$$Entropy\ (E) = \sum_{j=0}^{255} P_j(-\ln P_j) \quad (7)$$

In equation (7), j is the absolute set of pixel values and Pj is the probability that a particular pixel value appears in a given image.

BRISQUE: BRISQUE means "Blind/ Referenceless Image Spatial Quality Evaluator". BRISQUE is used to determine the reference-less quality score of an image. BRISQUE compares the image to a pre-defined (standard or custom) model created from images of naturally occurring environments with equivalent aberrations. A lower score indicates higher quality.

NIQE: NIQE stands for "naturalness image quality evaluator." It measures the extent to which an image appears natural to human perception without relying on a reference image. A lower NIQE score indicates higher quality, suggesting that the image exhibits a higher level of naturalness and realism.

PIQE: PIQE is an abbreviation for "perception-based image quality assessment." PIQE determines the reference-less quality value of an image. A lower score indicates higher quality.

A quantitative comparison between different performance evaluation parameters and the proposed method is shown below

TABLE I. COMPARISON OF THE ALGORITHM'S PERFORMANCE MEASURED USING SEVERAL METRICS

Method	Entropy	NIQE	PIQE	BRISQUE
Input Image	5.5528	4.2956	40.7888	40.5045
DSIHE [7,9]	6.127	5.2563	47.4298	42.0642
CLAHE [8]	6.2509	4.3828	42.8057	40.1465
BBHE [10]	6.127	5.2563	47.4298	43.064
RMSHE [6]	5.831	4.5702	45.5095	40.6386
BBHE–CLAHE Fusion	**5.4513**	**4.2559**	**41.0314**	**40.8003**
BBHE–RMSHE Fusion	6.1192	5.1737	48.2357	44.5
BBHE– DSIHE Fusion	5.8987	8.1792	53.4573	51.4346
CLAHE–RMSHE Fusion	**6.2516**	**4.3822**	**42.8173**	**40.14**
RMSHE–DSIHE Fusion	6.1677	5.3476	48.2531	44.3276

After applying the proposed method, the processed MRI images are analyzed based on metric parameters such as entropy, NIQE, BRISQUE, and PIQE. The amount of unpredictability in the processed MRI image is assessed using the metric parameter entropy, which reveals details about the texture of the image. Therefore, it can be concluded that if the entropy value of the output image is high, the result is desirable. NIQE compares the quality of the processed image with the quality of the input image calculated from the natural landscape. Therefore, a lower NIQE value indicates a higher processed image quality. The PIQE metric computes the distortion of spatially significant image regions. Images with smaller PIQE values are of better quality. BRISQUE evaluates image attributes by evaluating locally normalized luminance coefficients. Therefore, images with lower BRISQUE scores are of higher quality.

After taking the values of the above metric parameters for the processed images and comparing them with those of the original image, some interesting results are observed. Combining different HE techniques has been found to provide better performance than applying a single histogram equalization technique to the processed image. The CLAHE-RMSHE fusion has obtained the most outstanding value among all the proposed fusion methods. The image entropy value increased from 5.5528 to 6.2516. NIQE, PIQE and BRISQUE also have promising values of 4.3822, 42.8173 and 40.14 respectively.

C. Region Of Interest

Regions of interest (ROIs) highlighting in MATLAB refers to the process of emphasizing specific regions or objects of interest within an image. This can be achieved using techniques such as threshold-based methods, image segmentation, or saliency-based approaches. These methods help improve the visibility and perceptual significance of important image content for subsequent analysis.

ROIs are manually highlighted in MATLAB to locate tumor sites in brain images precisely. This process is called manual segmentation

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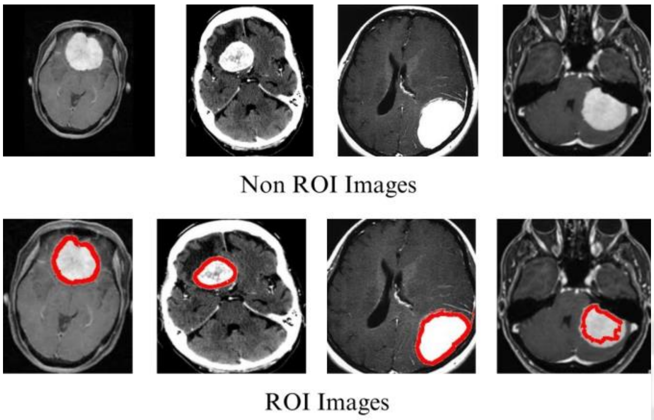

Figure 4: Original Dataset Sample Images with and without the Region of Interest (ROI) highlighted

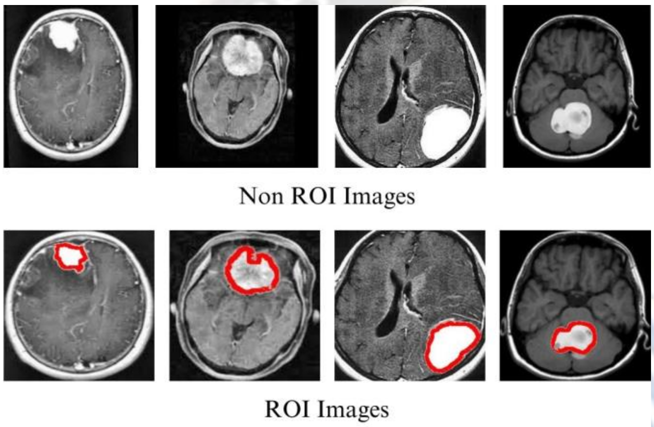

Figure 5: CLAHE-RMSHE Fusion Enhanced Sample Images with and without the Region of Interest (ROI) highlighted

The segmentation of ROI in the above images makes it easier for the machine learning models and techniques that are further applied to correctly identify where the tumor is located in the entire image, thereby vastly improving accuracy and efficiency of detection.

D. Classification

Classification in machine learning is a technique used to categorize or label data into predefined classes or categories based on their features.

In the context of tumor and non-tumor MRI image classification, machine learning can be used to identify and classify images as either tumor or non-tumor automatically. The process involves extracting relevant features from the MRI images, such as texture, shape, or intensity characteristics. These features are then used to train a classification model, such as a support vector machine (SVM), random forest, or convolutional neural network (CNN).

Several classification methods are applied to the MRI images to classify them into tumor and non-tumor images. The accuracy of these classifications can help to judge the improvement in detection post enhancement.

Convolutional Neural Network (CNN): It is a class of deep learning algorithms frequently used in computer vision applications. It involves using convolutional layers to detect features present in images, which is particularly effective for tasks such as image classification and object detection.

Support Vector Machines (SVM): It is an algorithm in machine learning used to find an optimal hyperplane that can be used to segregate different classes present within data with the widest margin, and is used for classification and regression analysis on both linear and nonlinear datasets.

Residual Network (ResNet): It is a deep learning architecture that introduces the concept of residual blocks. This makes it possible to effectively train very deep neural networks and use them in a plethora of different computer vision tasks, such as object recognition and image classification, and achieve state-of-the-art results.

Random Forest. It is a machine learning algorithm that uses ensemble learning to combine many decision trees to generate predictions and enhance accuracy. It is widely used in various applications such as classification, regression, and feature selection.

K-Nearest Neighbors (KNN): It is a nonparametric machine learning algorithm that predicts the class of a new data point based on the majority class of the nearest k neighbors in the training set. It is commonly used for classification and regression tasks.

Decision Trees. These are machine learning algorithms that build tree-like models of decisions and their possible outcomes, commonly used for classification and regression tasks. The model is built by recursively dividing the dataset into subsets based on the most discriminating features until a stopping criterion is met.

The results of classification are shown in the table below. The findings also confirm the results of enhancement:

TABLE II. COMPARISON OF CLASSIFICATION ACCURACY OF VARIOUS TECHNIQUES APPLIED ON THE ALGORITHM(S)

Method	CNN [21]	SVM [22]	RESNET [23]	Random FOREST [24]	KNN [25]	Decision TREES [26]
Original Images	71.6	93.4	98	96.13	89.6	90
DSIHE [7,9]	60.6	92.8	98.4	96.8	90.4	93.2
CLAHE [8]	62.99	92.8	96.6	97.33	91.2	93.8
BBHE [10]	60.19	92.8	97.69	95.87	93.8	84.4
RMSHE [6]	59.2	92.8	97.6	94.8	87.6	86.4
BBHE–CLAHE Fusion	**73.79**	**93.6**	**98**	**97.33**	**90.8**	**91.2**
BBHE–RMSHE Fusion	66.2	92.2	97.8	97.2	92.2	94.6
BBHE–DSIHE Fusion	59.6	92.8	98.5	96	91	88.6
CLAHE–RMSHE FUSION	**79**	**92.8**	**98**	**97**	**91.2**	**93.8**
RMSHE–DSIHE Fusion	59.2	92.2	97.5	96.93	91.6	92.2

Next, the various classification techniques described above are applied to a smaller set of MRI images with tumors marked using ROI. This set consists of 100 tumor images with ROI marked and 100 non tumor images. ROI segmentation has been applied to the original as well as CLAHE-RMSHE fusion enhanced images.

The following table shows the classification accuracy for the sample dataset [28,28] using different classification algorithms:

TABLE III. COMPARISON OF DETECTION ACCURACY OF VARIOUS TECHNIQUES APPLIED ON THE ALGORITHM(S)

Method	Original	CLAHE-RMSHE Fusion
CNN	52.49	60.00
SVM	80.00	95.00
Random Forest	83.33	83.33

The table above shows the accuracy of different classification algorithms for both the original images and the proposed method. Compared with the original image, the proposed ROI highlighting method improved the accuracy of most of the algorithms. For example, the support vector machine (SVM) algorithm achieved 80% accuracy for the original image and 95% accuracy for the proposed method.

These results suggest that the proposed ROI highlighting technique effectively enlarged the tumor area and consequently improved the classification accuracy. Furthermore, the high accuracy of the algorithm of the proposed method indicates that it may improve tumor detection accuracy in MRI brain scans. Therefore, the step of highlighting the ROI is critical to precisely localize the tumor site on the MRI scan, and the subsequent classification analysis evaluates the effectiveness of the proposed strategy in reliably detecting the tumor.

V. CONCLUSION

In this research paper different histogram equalization methods are executed on the given input picture of MRI and Furthermore, these methods are employed in conjunction with each other on the identical input images. Image combination refers to the process of merging relevant information from multiple pictures into a unified image. The resultant image will be more informative than any of the original pictures, as it retains the essential highlights from each of them. The resulting picture contains more data as compared to input images.

After evaluating various metrics, it is observed that the CLAHE-RMSHE fusion gives the best results, achieving an entropy value of 6.2516 and a BRISQUE value of 40.14. Additionally, the BBHE-CLAHE fusion has a high entropy parameter with a value of 5.4513.

This approach has the potential to improve the identification of valuable and fundamental components within MRI and CT images. It can facilitate the detection of tumors in the diagnostic process.

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