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The Srgb Color Space Based Density Analysis for Brain Tumor Segmentation

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Abstract

One of the important areas of study in medical image processing is early disease detection and diagnosis. A subfield of medical image processing includes the brain tumour segmentation procedure. Medical professionals have an efficient means of diagnosing illnesses because to computer vision and machine learning technology. The Srgb based density analysis is used in this study to isolate the area of brain tumours in MRI images. To differentiate the tumour area from the surrounding area, the intensity values of the input are normalised using the Gaussian filter and the Srgb colour space. In brain MRI samples, the adaptive threshold approach aids in locating potential tumour space. By calculating region parameters like area and density function, the actual space occupied by brain tumours is recovered. Ultimately, by applying morphological functions and removing potential false positives, the accurate tumour space is identified. Recall, accuracy, and F-measure are a few of the performance indicators that are used to evaluate how effective the suggested strategy.

Keywords: *Srgb color space, Gaussian Filter, Morphological functions.*

1. Introduction

The brain is acknowledged as one of the human body's most vital organs in the field of medical study because it helps process and regulate every bodily function. Cancer is the deadliest disease that can affect every organ in the human body by promoting the creation of aberrant cells. There are 200 different varieties of cancer that can afflict the human body as a result of various reasons. As a result, cancer is regarded the deadliest disease on a global scale. According to the American Cancer Association, approximately 80000 Americans had treatment for primary brain tumors in 2019, and nearly 16000 died from tumor[1]. Brain tumors are one of the most common central nervous system illnesses. They can have catastrophic consequences for human activity, including death. Gliomas have the highest mortality and morbidity rates of any intracranial tumor. Several imaging techniques have been tested using sophisticated technology to detect brain tumors. Magnetic resonance imaging (MRI) and computed tomography (CT) scans are the two most commonly used procedures for diagnosing brain tumor issues. Magnetic resonance imaging (MRI), a semi-imaging technology, generates structural pictures in three components. It is frequently utilized in the early detection, diagnosis, and monitoring of ailments. It is based on cutting-edge technology that stimulates and detects abruptness in the rotating area of protons found in the water that forms tissues.

2. Related Work

An overview of deep cognition techniques for tumour recognition and segmentation was given by Somasundaram and Gobinath [1]. This evaluation also examines more recent advances in deep neural network-based MRI image patch processing and classification for brain tumours. Lathera and Singh [2] examine brain tumour segmentation and detection techniques that have been suggested recently by other researchers. Additionally, a table-format summary of methods for fully and partially robotic brain tumour detection is provided in this page. The U-net model for robotic brain tumour isolation was developed by Yang and Song [3]. To extract the precise tumour location in a brain MRI sample, an optimisation

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technique is combined with loss functions to build the U-net architecture. To precisely identify the brain tumour space in MRI data, Ganasala et al. [4] employed a semi-automatic brain tumour segmentation technique. This method yields results that are quite comparable to those of an experienced radiologist. Quantitative criteria are used to assess this method. A method for medical image processing to identify tumours in brain samples was proposed by Gobhinath et al. [5]. The brain MRI sample's quality is improved by applying the median preprocessing concept and the high pass preprocessing concept to eliminate parts that aren't needed. A CAD system for automatic brain tumour identification and isolation was created by Akram and Usman [6]. This diagnostic method helps identify the tumour site by using accurate segmentation. Using DAPP for the brain, Jemimma and Vetharaj [7] put the watershed notion into practice. The watershed approach was utilised by Wulandari et al. [9] to ascertain the region of the brain tumour. To improve the MRI sample's quality, the median idea is applied. The exact location of the brain tumour region is ascertained by applying the thresholding technique. For the purpose of brain tumour segmentation, Hasan and Ahmad [10] suggested a two-step verification procedure based on the watershed method. Through the use of a matching technique, the tumour space in MRI samples was identified by this model and compared to the ground truth. Segmenting brain tumours using a semi-automated approach was created by Solomon et al. [11]. Using a probabilistic approach, the data-driven model extracts the brain tumour from the photos. The function of CNN in the segmentation of brain tumours is examined by Bhandari et al. [12]. Based on AResU-Net, Zhang et al. [13] created a tumour isolation network. When utilising U-net design, residual units help to increase the precision of identifying brain tumour locations in MRI images. Modern pattern recognition techniques for brain tumour segmentation in mpMRI samples are demonstrated by Bakas et al. [14]. The best learning model for brain tumour isolation in BRATS challenges is also determined by this study. An original model for brain tumour isolation was put forth by Hu et al. [15]. A random field and multi-cascaded convolutional neural networks are combined to construct this model. Competitive performance was produced by the experimental outcomes. A combination of two segmentation techniques was developed by Ali et al. [16] and is applied to brain tumour isolation. The combination of the 3D CNN with U-net architecture yields more precise and superior outcomes. A semi-automated brain tumour segmentation method based on graph cuts was created by Ramya and Jayanthi [17]. On graph cuts, the kernel mapping technique is utilised to identify the region of a brain tumour and separate numerous regions. An effective integrated model for brain tumour segmentation was developed by Singh et al. [18]. The tumour zone is distinguished from the non-tumor region using the SFCM spatial concept.

3. Proposed Methodology

The segmentation of brain tumours is one aspect of medical image processing. The brain tumour segmentation process, whether automated or computerised, helps doctors diagnose patients in the right channel. Consequently, this proposed technique for separating the tumour region in brain MRI scans consists of three steps. To lower the intensity levels, the input image is first preprocessed in a conventional RGB colour space. The tumour region is normalised into a uniform distribution by applying the Gaussian filter to the Srgb space image's gray-level. By comparing the preprocessed findings to the threshold value, the probable tumour region is found in the second stage. Region characteristics such as size and density are employed in brain MRI to identify the actual tumour space.

3.1. Preprocessing Using Color Space and Gaussian Filter

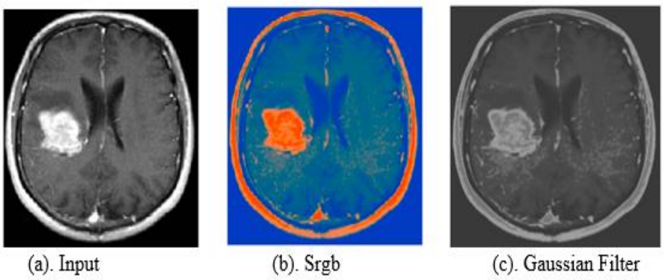

Figure 1 Outcome of Srgb and Gaussian Filter

The color value of an image provides additional semantic information about objects and background

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scenes. As a result, image processing algorithms rely on color spaces as well as specific features to perform effective picture operations. Converting from one color space to another requires conceptual understanding of color space features as well as application-specific constraints. Figure 1 depicts the outcome of the Srgb and Gaussian filters.

3.1.1. Color Space

To portray linear combination colour values into non-linear combination colour values, the current colour space shown in Figure 1(a) is modified to Standard RGB (Srgb) in this proposed approach. This provides a more user-friendly way to categorise the necessary space in brain MRI data. The gamma correction technique is one of the nonlinear functions that the srgb methodology applies to the existing colour space. This method helps to differentiate between the colour representation in brain MRI images. As can be seen in Figure 1(b), the tumour region appears brighter than the background region due to the Srgb colour scheme. Equations 1, 2, and 3 are the parameters used to convert the current colour system to Srgb space.

$$f(x) = -f(-x), \quad x < 0 \tag{1}$$

$$f(x) = n \cdot x, \quad 0 \leq x < q \tag{2}$$

$$f(x) = l \cdot x^p + m, \quad x \geq o, \tag{3}$$

Where u represents one of the R, G, or B color values with these parameters:

l = 1.055

m = –0.055

n = 12.92

q = 0.0031308

p = 1/2.4

3.1.2. Gaussian Filter

Since the Srgb method sharpens the high frequency component of tumour pixels, the tumour region's pixels are smoothed using a Gaussian filter. As shown in Figure 1(c), the Gaussian filter (equation 4) is a low pass filter that reduces noise by adding blurriness to the image region. To apply this method, the effective gap between tumour and non-tumor pixels is calculated by processing each pixel in the image using a symmetric kernel. Since the central pixel of the symmetric kernel has a higher weightage towards the final value, the symmetric kernel alters the colour information.

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{4}$$

3.2. Possible Tumor Region Extraction

Thresholding technique is utilised to derive the probable tumor location by comparing each pixel of the brain MRI data to the computed value. A common method for dividing the area of interest from the backdrop is thresholding. Similarly, equation 5 is used to determine the threshold value. Subsequently, the computed threshold value th is compared with each pixel value of the Gaussian blurred output. In the Gaussian blurred output, this separates all of the pixels into two sets: those whose intensity levels are below the threshold and those whose intensity levels are above the threshold. Since the pixel intensity level in the tumour zone is higher than the background intensity level, the suggested method accounts for pixel values larger than the threshold value. It generates the binary in the end. (refer Figure 2)

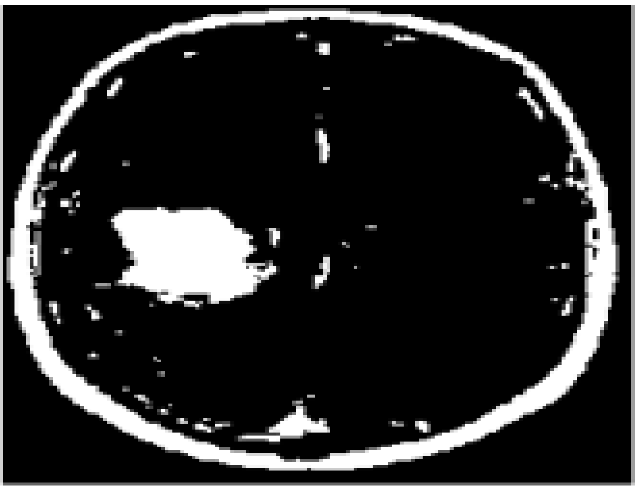

Figure 2 Extraction of Possible Tumor Region

$$t0 = 0.1$$

$$th = \frac{t0 + \left(\max\left(G(x,y)\right) + \min\left(G(x,y)\right)\right)}{2} \tag{5}$$

3.3.3.3 Detection of Actual Tumor Region

By evaluating the potential tumour zone's characteristics, the true tumour region is identified. In brain MRI samples, region-based metrics such area and stiffness are examined to ascertain the true shape and location of the tumour space. The precise number of intensities found in potential tumour samples is determined by the area region attribute. Applying a

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convex polygon to a likely tumour site yields the convex area. By dividing the area by the convex area, solidity computes the density of the tumour region while preserving the real tumour region. Finally, the actual tumor region is extracted by intersecting the solidity image result with the possible tumor region, as depicted in Figure 3.

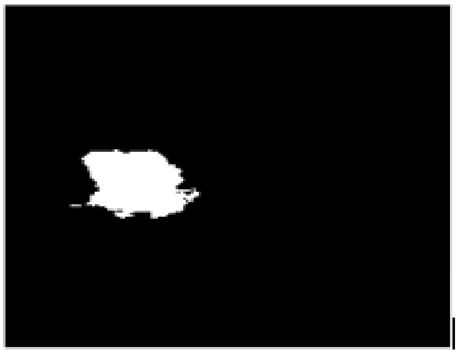

Figure 3 Outcome of Actual Tumor Region Extraction

3.4. Post Processing for Eliminating Unwanted Regions

After extracting the real tumor site, some undesired regions were found in the tumor detection image. As a result, morphological techniques such as dilation and filling are used to eliminate potentially undesired regions. The dilate procedure unites all of the unconnected tumor pixels. The filling procedure puts pixels into the gaps formed in the tumor zone, resulting in a complete tumor area as illustrated in Figure 4.

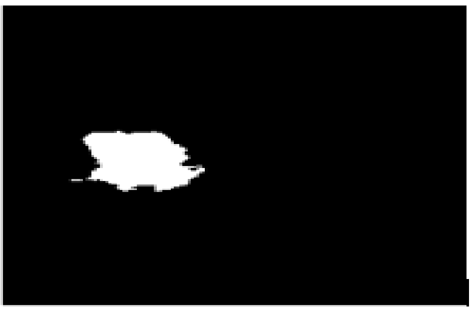

Figure 4 Tumor Region Detected

4. Results

To evaluate the suggested methodology, a comprehensive experimental analysis is performed on the Kaggle brain tumor MRI dataset. Which is available for public download at "https://www.kaggle.com/navoneel/brain-mri images-for-brain-tumor-detection". This dataset includes two separate brain MRI classes: Yes and No. The Yes class reflects the existence of a tumor region in brain MRI samples, while the No class shows the lack of a tumor region in brain MRI samples. This dataset contains 253 brain MRI pictures with a standard size of 240x240 pixels. Out of 253 brain MRI pictures, 155 have a tumor area and 98 do not. Figure 5 shows sample outcomes from the proposed technique.

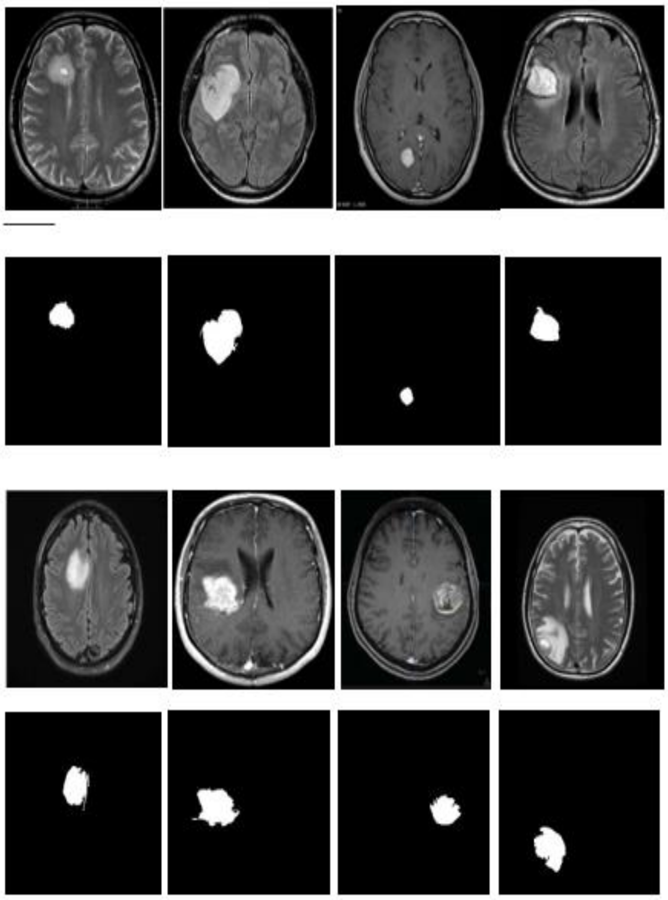

Figure 5 Sample Outputs of Proposed Methodology

The evaluation metrics for the proposed technique are: Recall (R) (Equation 6): Truly Detected Tumor Region (TDTR) vs. Actual Tumor Region (ATR). Precision (P) (Equation 7) is the difference between the Truly Detected Tumor Region (TDTR) and the

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Falsely Detected Region (FDR). F-Measure (Equation 8): The product of Recall and Precision over their sum.

$$Recall\ (R) = \frac{TDTR}{ATR} \quad (6)$$

$$Precision(P) = \frac{TDTR}{TDTR + FDR} \quad (7)$$

$$F - Measure = \frac{2 * R * P}{R + P} \quad (8)$$

Table 1 Evaluation of Proposed Methodology

Classes	Precision	Recall	F-measure
Yes	90.14	83.11	86.48
No	89.53	78.57	83.69
Average	**89.83**	**80.84**	**85.08**

Table 2 Comparative Analysis of Proposed Methodology

Methods	Precision	Recall	F-measure
K-Means [19]	0.83	0.64	0.72
K-Means with PSO [19]	0.86	**0.82**	0.84
DWT+PCA+SVM(Linear) [20]	0.40	**1**	0.57
Proposed Methodology	**89.83**	80.84	**85.08**

Table 1 shows the analysis results for both classes using the recommended methodology. The semantic difference between the tumour region and the non-region is effectively expanded by the Srgb colour scheme. Additionally, morphological functions remove any false positives, increasing precision. To show the overall effectiveness of the recommended strategy, separate result analyses for the yes and no courses were carried out and averaged results were produced, as shown in Table 1. The provided strategy is compared to earlier state-of-the-art methods in Table 2. The obtained results excel in terms of precision and the f-measure, but they are competitive in recall. [19,20]

Conclusion

Automated brain tumor segmentation algorithms enable medical practitioners diagnose patients in the right channel. As a result, the current recommended methodology uses the Srgb color space with a Gaussian filter. Srgb can efficiently discriminate tumor intensity measurements from non-tumor intensity levels. The Gaussian filter is useful for smoothing the pixels of the tumor region. Later, the threshold value totally distinguishes tumor pixels from non-tumor pixels and is deemed a probable tumor location. The area and density of region attributes efficiently identify the correct tumor region. Morphological functions can help to remove any false positives in the final outcome. In the future, post-processing techniques will be investigated to isolate the real tumour location from complex MRI images.

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