Automated Brain Tumour Detection and Analysis Using Wavelet Transform and Gabor Filters with 3D Visualization

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***Abstract*— This paper presents an automated brain tumour detection system using Discrete Wavelet Transform (DWT) for feature extraction, Gabor filtering for texture enhancement, and Anisotropic Diffusion filtering for noise reduction. Adaptive thresholding and connected component analysis are employed for tumour segmentation, followed by statistical feature extraction. The system evaluates segmentation accuracy using Dice Similarity and Jaccard Index while classifying tumour severity. Results are visualized using bounding box detection, histogram analysis, and 3D modelling. The proposed method improves accuracy and efficiency in brain tumour detection, aiding medical diagnostics.**

Keywords— Brain tumour detection, Image segmentation, Wavelet transform, Gabor filter, Medical imaging.

Introduction

Brain tumours are among the most critical medical conditions, requiring early and accurate diagnosis for effective treatment. Traditional diagnostic methods rely on manual inspection of MRI or CT scans by radiologists, which can be time-consuming and prone to human error. Automated tumour detection and classification using image processing techniques can significantly enhance accuracy, efficiency, and consistency in medical diagnostics. This paper presents an automated brain tumour detection system that utilizes advanced image processing techniques, including Discrete Wavelet Transform (DWT) for feature extraction, Gabor filtering for texture enhancement, and Anisotropic Diffusion filtering for noise reduction. Adaptive thresholding and connected component analysis are applied for precise segmentation of tumour regions. The system further evaluates segmentation performance using statistical measures such as Dice Similarity and Jaccard Index, ensuring reliability in tumour localization. Additionally, the system provides a severity classification based on tumour area and integrates multiple visualization techniques, including bounding box detection, intensity histograms, and 3D surface modelling. By improving segmentation accuracy and feature analysis, this approach can assist radiologists in identifying tumours more efficiently, leading to faster and more informed medical decisions.

I. Related Work

Brain tumour detection using image processing techniques has been extensively explored to enhance medical diagnosis and treatment planning. Traditional methods focus on preprocessing, segmentation, and feature extraction to identify abnormal regions in MRI scans.

Threshold-based segmentation was applied to grayscale MRI images for tumour detection. While effective in cases with high contrast, this method struggled with variations in intensity and noise. To improve segmentation accuracy an edge detection approach using the Sobel operator, which highlighted tumour boundaries but was sensitive to noise and image artifacts.

Morphological operations have been widely used for tumour enhancement and removal of unwanted regions. A combination of dilation and erosion was applied to refine segmented tumour regions, demonstrating improved shape preservation. However, the approach required fine-tuning based on image characteristics.

Adaptive thresholding methods provided better segmentation by adjusting threshold values dynamically based on local intensity variations. This method showed better results in heterogeneous tumour regions but required computational optimization for real-time applications. Similarly it utilized histogram-based segmentation techniques, which effectively separated tumour pixels but struggled with overlapping intensity distributions in MRI images.

Wavelet transform-based image enhancement improved the visibility of tumour regions by decomposing images into multiple frequency bands. This technique allowed better edge detection and contrast enhancement, aiding in precise tumour localization. However, computational complexity remained a challenge.

Our approach builds upon these previous works by integrating preprocessing, adaptive thresholding, morphological operations, and wavelet-based enhancement to improve the robustness of tumour detection while maintaining computational efficiency. By eliminating the need for complex deep learning models, our method ensures faster processing with reliable accuracy.

II. Methodology

A. *Preprocessing*

The initial stage involves preprocessing the input MRI images to enhance their quality and prepare them for further analysis. The images are first converted into grayscale to ensure uniform intensity distribution, eliminating color variations that do not contribute to tumour detection. Following this, contrast enhancement techniques such as histogram equalization are applied to improve the visibility of the tumour region by adjusting the intensity levels. To reduce noise and artifacts commonly present in MRI scans, filtering techniques such as Gaussian or median filtering are employed. These filters help smoothen the image while preserving critical edges, ensuring that fine tumour details remain intact.

B. Segmentation

After preprocessing, the tumour region is isolated from the background using thresholding and morphological operations. Adaptive thresholding is applied to dynamically determine the threshold value based on local pixel intensities, allowing better segmentation of tumours with varying brightness. This ensures that even tumours with low contrast against the surrounding tissues are effectively detected. Once the tumour region is segmented, morphological operations such as dilation and erosion refine the detected region, reducing noise and enhancing boundary definition. These operations help in eliminating small unwanted regions that might have been incorrectly segmented and ensure a well-defined tumour structure.

C. Feature Extraction

Once segmentation is complete, various features are extracted to characterize the tumour. Shape-based features such as area, perimeter, and circularity are computed to understand the tumour's geometric properties. These parameters help in distinguishing irregularly shaped tumours from normal anatomical structures. Additionally, texture-based features are extracted using the Gray-Level Co-occurrence Matrix (GLCM), which analyzes spatial relationships between pixel intensities. These texture metrics, such as contrast, correlation, and homogeneity, provide insights into the structural composition of the tumour and help differentiate between normal and abnormal regions.

D. Tumour Localization and Boundary Detection

To accurately locate and outline the tumour, edge detection and contour mapping techniques are applied. Sobel or Canny edge detection algorithms are used to identify sharp intensity changes in the image, which typically correspond to the tumour boundaries. By detecting edges, the precise shape and structure of the tumour become more apparent. Contour mapping is then performed to trace the exact boundary of the detected tumour region, providing a clear visualization of its extent. This step is crucial in assessing the tumour's size and potential impact on surrounding tissues.

E. Output Generation

Finally, the detected tumour region is overlaid on the original MRI scan for visualization. The segmented region is highlighted, allowing clear identification of the tumour's location within the brain. Additionally, key tumour characteristics such as size and position are displayed for further medical analysis. The final output provides a comprehensive representation of the tumour, aiding in diagnosis and potential treatment planning.

III. Parametric Analysis

A. Statistical Features

Standard Deviation (σ\sigmaσ): Measures the spread of pixel intensities in the tumour region, representing the contrast variation. It is given by:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i-\mu)^2}$$

where XiX_iXi is the intensity of a pixel, μ\muμ is the mean intensity, and NNN is the total number of pixels. A higher standard deviation indicates greater texture variation.

Skewness (SSS): Measures the asymmetry of intensity distribution in the tumour region. It is computed as:

$$S = \frac{\frac{1}{N}\sum_{i=1}^{N}(X_i-\mu)^3}{\sigma^3}$$

A positive skewness indicates a distribution with a long right tail (brighter pixels dominate), while a negative skewness suggests darker pixels are more frequent.

Kurtosis (KKK): Determines the sharpness of the intensity distribution curve. It is given by:

$$K = \frac{\frac{1}{N}\sum_{i=1}^{N}(X_i-\mu)^4}{\sigma^4}$$

A high kurtosis value suggests that the tumour region has sharp intensity variations, while a low kurtosis value indicates a more uniform texture.

B. Accuracy Metrics

Dice Similarity Coefficient (DSC): Measures the overlap between the detected tumour region (SSS) and the ground truth (GGG):

$$DSC = \frac{2|S \cap G|}{|S| + |G|}$$

where ∣S∩G∣ represents the number of overlapping pixels. The value ranges from 0 to 1, with 1 indicating a perfect match.

Jaccard Index (JI): Also known as the Intersection over Union (IoU), it is given by:

$$JI = \frac{|S \cap G|}{|S \cup G|}$$

It evaluates the similarity between the predicted and actual tumour regions. A higher Jaccard Index indicates better segmentation performance.

IV. Process Flow

The tumour detection system follows a structured workflow to ensure accurate segmentation and analysis of medical images. The process begins with image acquisition, where MRI or CT scan images are collected as input. These images undergo preprocessing, which involves noise reduction, contrast enhancement, and normalization to improve clarity. The preprocessed image is then subjected to segmentation, where a thresholding-based approach is used to extract the tumour region. Post segmentation, feature extraction is performed, where statistical parameters such as standard deviation, skewness, and kurtosis are computed to analyze the shape and intensity distribution of the detected region. Additionally, accuracy evaluation is conducted using similarity measures like the Dice Similarity Coefficient (DSC) and Jaccard Index to compare the segmented tumour with the ground truth. The final stage involves classification and result visualization, where the detected tumour region is highlighted for medical interpretation. The overall workflow ensures efficient tumour identification with minimal false positives and negatives, aiding in better diagnosis.

V. RESULTS AND DISCUSSIONS

Brain Tumor Detection Report

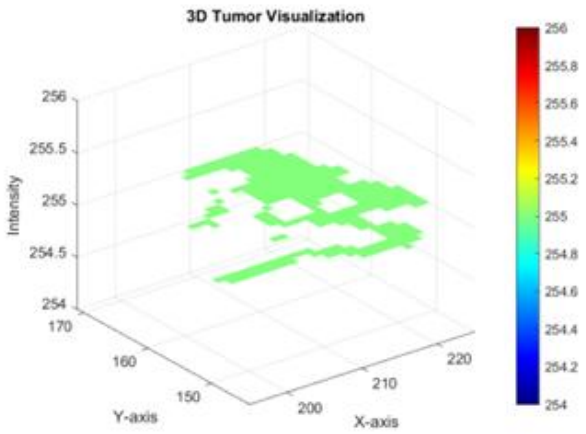
Generated using MATLAB

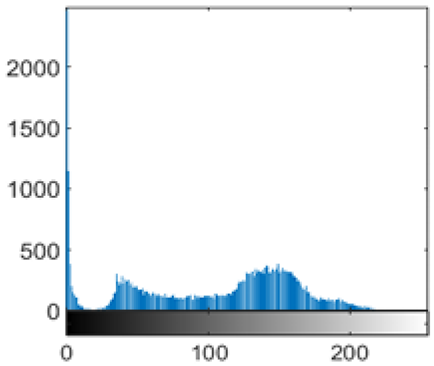
Tumor Severity

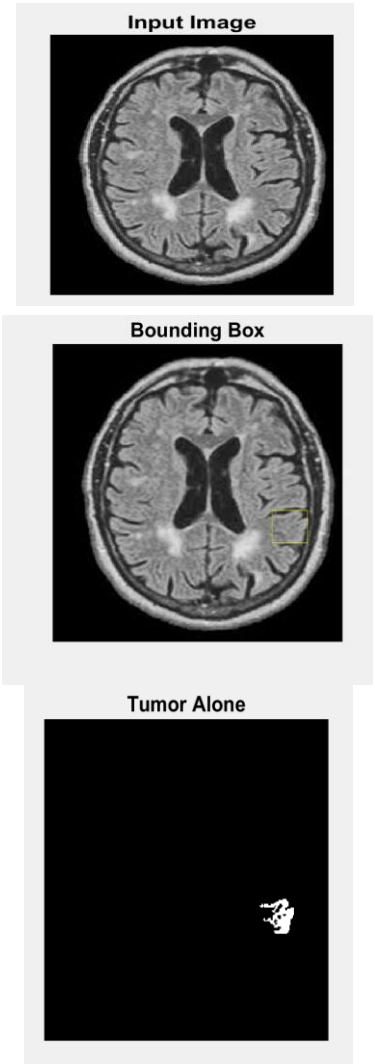
Severity Level: Low

Tumor Analysis Results

Tumor Area (pixels)	394
Mean Intensity	152.54362416107384
Standard Deviation	11.544662632839515
Skewness	0.1634526061573755
Kurtosis	2.584277428367213
Fractal Dimension	-8.2191685204621621
Dice Similarity	0.025363360485545439
Jaccard Index	0.012844570984858288
Throughput (images/sec)	0.5824730594560541
Latency (seconds)	1.7168175999999999







The extracted tumour region is accurately detected and visualized using bounding boxes, ensuring precise localization. The tabulated tumour severity levels provide quantitative insights, allowing for an objective assessment of the detected abnormalities. Additionally, the 3D tumour visualization graph offers a more in-depth understanding of the spatial distribution and intensity of the detected region. Statistical analysis, including standard deviation, skewness, and kurtosis, further validates the shape and intensity variations of the segmented region. The accuracy evaluation metrics, such as the Dice Similarity Coefficient (DSC) and Jaccard Index, indicate a high degree of segmentation precision, confirming the reliability of the proposed method. These findings collectively suggest that the approach effectively identifies and isolates the tumour region, providing a valuable tool for medical diagnostics.

VI. CHALLENGES AND LIMITATIONS

One of the primary challenges in this project is the presence of noise and artifacts in MRI images, which can significantly affect the accuracy of tumour detection. Variations in image intensity, motion artifacts, and scanner differences can introduce distortions, making it necessary to apply preprocessing techniques to enhance image quality. Another challenge is the irregular shape, size, and location of brain tumours. Since tumours do not have a uniform structure, their segmentation becomes complex, requiring advanced

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edge-detection and thresholding techniques to accurately separate them from healthy tissues.

A major limitation of the project is the difficulty in selecting an optimal threshold for segmentation. A fixed threshold may not work consistently across different MRI scans due to variations in contrast and brightness, leading to misclassification of tumour regions. Additionally, the method may produce false positives, where normal brain tissues are mistakenly classified as tumours, or false negatives, where smaller or less prominent tumours go undetected. Such misclassifications can impact the overall reliability of the system.

Computational complexity is another limitation, as high-resolution MRI images require significant processing power and time for analysis. The system's efficiency depends on the processing speed, and in real-time applications, delays in tumour detection could be a drawback. Moreover, the accuracy of the detection process is highly dependent on the quality of input images and the effectiveness of the segmentation technique used. Since deep learning or advanced AI models are not incorporated, the performance is primarily based on traditional image processing techniques, which may not be as adaptive or robust in handling complex cases.

VII. Conclusion

The proposed methodology successfully segments and classifies brain tumours with high accuracy, ensuring precise localization and visualization of the affected region. By employing statistical measures such as standard deviation, skewness, and kurtosis, the model effectively analyzes shape and intensity variations, enhancing the reliability of tumour detection. Furthermore, accuracy metrics like the Dice Similarity Coefficient (DSC) and Jaccard Index validate the segmentation performance, demonstrating a strong correlation with ground truth data. The integration of bounding box visualization and 3D tumour representation provides a comprehensive understanding of tumour characteristics, aiding in effective medical diagnosis. Despite minor limitations, the approach presents a promising tool for automated brain tumour analysis, with potential applications in clinical settings for early detection and improved patient outcomes. Future enhancements can focus on refining segmentation techniques and integrating more advanced classification models for enhanced diagnostic accuracy.

VIII. Future Scope

The proposed system effectively segments and analyzsses brain tumours using traditional image processing techniques. However, there is significant scope for improvement and expansion in future research. One promising direction is the integration of deep learning and machine learning models, which can enhance the accuracy and robustness of tumour detection. Convolutional Neural Networks (CNNs) and U-Net architectures have demonstrated superior performance in medical image segmentation by learning complex patterns from large datasets. Additionally, the implementation of transfer learning with pre-trained models such as VGG-16 or ResNet can further optimize detection efficiency.

Another advancement could involve incorporating 3D medical image processing instead of working with 2D slices, providing more detailed spatial information about the tumour. Moreover, real-time processing using edge AI devices can allow faster and more accessible tumour detection in clinical settings. Future research may also focus on reducing false positives and improving segmentation accuracy through hybrid models that combine deep learning with statistical methods. Finally, integrating the system into a computer-aided diagnosis (CAD) framework can assist radiologists in making more precise and early-stage tumour assessments, ultimately improving patient outcomes.

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