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Improved Brain Tumor Detection MRI Using Advanced Processing Techniques: Enhancement and Convolution Case Studies

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A B S T R A C T

Brain tumors present a significant challenge in medical imaging due to their complexity, requiring early detection and precise analysis for effective treatment. This study develops and evaluates advanced image processing workflows aimed at enhancing brain tumor image analysis. The proposed method involves four main steps: enlargement, pre-processing with min-max filters, enhancement, and convolution. The dataset used is from Kaggle, comprising 3,364 images categorized into Glioma (100 images), Meningioma (115 images), No Tumor (105 images), and Pituitary Tumor (74 images). For this study, images from the Glioma, Meningioma, and Pituitary Tumor categories were used, with one image selected from each category for technique evaluation. The results showed significant improvements in image clarity and detail, with high correlation values of 0.9851 for Meningioma and 0.9886 for Pituitary. These findings highlight the effectiveness of the proposed techniques in enhancing image quality and diagnostic accuracy.

1. Introduction

Tumors known as neoplasms, formed as a result of the uncontrolled growth of abnormal cells [1]. A brain tumor (cancer) is an abnormal mass of tissue that appears in the central spinal cord or brain, where some cells grow and spread uncontrolled, seemingly unregulated by natural processes that control normal cells [2]. Our brains are protected by a very tough skull. When a tumor grows rapidly in a limited space, the brain's natural function is disrupted. The primary cause of deadly cancer cells in the brain may be related to certain conditions such as excessive exposure to inorganic chemicals or genetic abnormalities [3].

Brain tumors can be benign (non-cancerous) or malignant (cancer) [4], [5], [6]. When a benign, pre-cancer, or malignant tumor grows, the pressure in the skull increases, causing a variety of problems for humans [7], [8]. It can cause serious and potentially life-threatening brain damage. Therefore, detection of brain tumors at an early stage is crucial to increasing the chances of human survival.

Various techniques have been proposed to predict the presence of tumors in the brain [9], [10], [11], [12]. Tumors in organs are generally divided into three types: Tumors on glial cells in the brain or spinal cord area (Glioma), a tumor that develops from a membrane that covers the brain and spinal cord (Meningioma), and tumors caused by abnormal growth in the pituitary gland (Pituitary) [13]. Medical imaging technology in the e-healthcare domain plays a crucial role in today's development of the field. Medical professionals face various obstacles in identifying malignant brain tumor cells [14], [15]. Early detection of brain tumors is now a critical task in medical science, given its status as the top ten cause of disease [16], [17]. Malignant tumors in the brain can appear in various locations with varying sizes and dimensions [18].

Generally, various techniques are used to produce images of the soft tissue of the human body in the analysis of medical images [19]. Magnetic Resonance Imaging (MRI) is one of the techniques used by medical professionals [20]. MRI is a non-invasive method used to analyze human brain tumor imaging data accurately to determine the condition of the patient [21], [22]. MRI technique is very useful because of the normalization of the tissue contrast and the high resolution of the image. Increased tissue contrast in MRI images refers to the improved differentiation between different types of tissue, which helps in better identifying and distinguishing abnormal tissues like tumors from normal brain tissues. With better contrast, doctors can see clearer and more accurate details of the structure and condition of the tissue examined. MRI images provide information about the genetics, physiology, chemistry, and biology of the abnormalities present in the brain

[23]. Tumors are classified according to their cell origin and properties. Primary tumors in the brain generally appear in the central hemisphere, while secondary brain tumors originate from other body organs to the brain. The most common primary brain tumors are glioma, meningioma, and pituitary tumors [24].

Gliomas typically originate from glial cells, which are supportive cells in the brain that include astrocytes, oligodendrocytes, and ependymal cells. These cells help in the normal functioning of brain neurons. Gliomas develop when these glial cells mutate and start to proliferate uncontrollably [25], [26]. Glial cells are supporting cells in the brain that include astrocytes, oligodendrocytes, and ependymal cells. Gliomas develop when these cells mutate and start to proliferate uncontrollably. The World Health Organization (WHO) classifies glioma as non-glioblastoma at degree II-III and as glioblastoma at degree IV [27]. Three types of normal glial cells can produce malignant tumors [28]. Astrocytoma tumors are produced by astrocyte cells (including glioblastoma), oligodendroglioma tumors are derived from the cells of the oncocytoma, and ependymomas appear from the ependymal cells [29]. A tumor involving a mixture of different glial cells is known as a mixed glioma. Meningioma, a type of tumor, comes from the brain membrane that protects the brain and spinal cord inside the skull. This tumor grows on a membrane layer called meninges [30]. Adenoma of the pituitary gland (tumor) appears abnormally in the hypophysis area located inside the skull, between the brain and the nasal tract [31]. Meningioma and pituitary tumors are benign and do not spread to tissues, cells, or other parts of the body. A glioma, on the other hand, is a malignant tumor that can spread to other organs of the human body [32].

Image classification is an important and broad field of research in deep learning and computer vision [33]. This process includes labeling an image into one of several previously defined classes. The classification covers several stages such as image data acquisition, image data pre-processing, image object detection, image segmentation, feature extraction, and image object classification [34]. In the domain of medical health care, image classification plays a crucial role in the field of biomedical imaging to detect and diagnose diseases accurately, which helps improve diagnostic efficiency for radiologists and provide better surgical treatment options [35].

In the context of tumor detection, the Watershed method has shown promise. For instance, in research [41], the Watershed method achieved a tumor area detection metric of 0.0621 with 3138 pixels and an execution time of 0.366 seconds. This suggests that the Watershed algorithm can be effective in accurately delineating tumor regions within MRI images, contributing to more precise and timely diagnosis.

This research will contribute to the understanding and development of the field of brain tumor detection using new technologies. By utilizing advanced processing techniques such as deep learning and medical image processing, this research aims to improve the accuracy and efficiency of early-stage brain tumor detection. Early detection is crucial to providing timely treatment and improving patient recovery chances. This study will explore various image classification methods and data augmentation techniques to enhance the quality and reliability of brain tumor detection and integrate new approaches in MRI image analysis to achieve better and more informative results.

2. Research Method

The research proposes an image-processing pathway to detect brain tumors that consists of four main stages of image enlargement, pre-processing, enhancement, and convolutions as shown in Figure 1. Each stage uses a special algorithm to deal with challenges in brain tumor image analysis, thereby improving the clarity and detail of the image to detect the brain tumor features more accurately. The image zoom stage focuses on zooming the image without losing important details. In the pre-processing phase, disturbing noise is removed to prepare a cleaner image for the next phase. Image magnification is done to highlight the important features of the brain tumor. Finally, convolutions are applied to extract specific characteristics of the tumor, which helps in more accurate diagnosis and analysis.

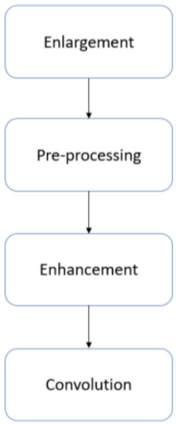

Figure 1. Research Workflow

2.1. Enlargement

Enlargement or image enlargement in brain tumor analysis is an important step in medical imaging processing to obtain better details of the tumor structure [36]. In the context of brain tumors, image magnification is used to enlarge the size of pixels proportionately, allowing for clearer and more accurate identification of small and subtle features in the MRI image. Image magnification is done using interpolation techniques, such as bilinear or bicubic, which estimate the values of new pixels based on their nearest neighbors.

Bilinear Interpolation: This method is chosen for its ability to produce smooth images with relatively simple calculations. Bilinear interpolation uses a weighted average of four nearest neighboring pixels to determine the value of a new pixel, making it effective in preserving details without introducing excessive artifacts. This is crucial in brain tumor analysis, where detail clarity is essential for accurate assessment.

Bicubic Interpolation: This method is used because it provides smoother and more detailed results compared to bilinear interpolation. Bicubic interpolation considers more neighboring pixels (16 pixels) for calculating the new pixel values, resulting in better edge preservation and texture details. In the context of brain tumor detection, the improved image quality with bicubic interpolation aids in analyzing complex and finer structural details.

This step is crucial in helping radiologists and neurosurgeons to evaluate tumor size, shape, and boundaries more accurately, which in turn supports more accurate diagnosis, better surgery planning, and monitoring response to therapy. Image magnification also facilitates the application of other advanced image processing techniques, such as segmentation and texture analysis, which are essential in the comprehensive characterization of brain tumors. The algorithm formula used for magnifying images in this study is presented at Equation (1).

$$b(i,j,m) = ((b\left(\frac{i-1,j,m}{2}\right) + (b\left(\frac{i+1,j,m}{2}\right))) \quad (1)$$

The equation (1) explains how each pixel in the enlarged image is calculated based on the values of its neighbor's pixels in the horizontal direction (i-1 and i+1). This process involves a rounding operation to ensure that the result is an integer since the representation of pixels in an image usually uses an integer. This rounding operation is important to maintain consistency in the resulting pixel values.

```
Pipeline algorithm
Input:
image_path,
num_images,
kernel

Output: Processed Images

  Initialization
  num_image = 10,
  kernel [0 2 0; 2 5 2; 0 2 0]
  For i = 1 to num_images do
      img = read_image(filename i)
      img = convert_to_greyscale(img)
      Im1 = lci_enlarge(filename i)
      Im2 = filter_min_max_gray(Im1)
      Im3 = Enh_gray(Im2)
      Img4 = konvolusi (Im3, kernel)

  Display Img4
End For
```

Figure 2. Pseudocode

2.2. Pre-processing

Pre-processing images of brain tumors with a min-max filter is an important step in medical image processing to improve visual quality and analysis accuracy [37]. Min-max filters are used to normalize image contrast by extending the pixel intensity range between the minimum and maximum values present in the image so that the entire dynamic range of pixels (0 to 255) can be optimally utilized [38]. This process helps in reducing the noise and variation of unwanted lighting, so that important features of the tumor such as size, shape, and boundary become clearer and easier to identify. By improving contrast and image detail, the min-max filter makes it easier for radiologists and neurosurgeons to analyze, detect, and plan more effective treatment for patients with brain tumors. For the types of tumors studied, glioma and meningioma images have a resolution of 796x702 pixels, while pituitary tumor images have a resolution of 800x800 pixels, after pre-processing. This min-max filter is formulated in equation (2).

$$G(i,j,c) = uint8((min(max(F(i,j,c), minC), maxC \quad (2)$$

Equation (2) briefly explains how each pixel is adjusted to ensure that its value is within the range of minimum and maximum values around it, thus effectively implementing the min-max filter. There is a possibility of using another algorithm to produce a different pre-processing process.

2.3. Enhancement

The enhancement method for brain tumor images improves contrast and clarity of detail and separates the tumor features from the background [39]. This involves several techniques to optimize pixel intensity and aid in accurate identification of the tumor structure. Improved contrast and sharpness are achieved through methods like histogram equalization, sharpening filters, and adaptive contrast adjustments, which make tumor features more visible against the background. Additionally, the Canny edge detection algorithm is utilized to highlight the tumor boundaries by detecting sharp edges with its multi-stage process that includes noise reduction, gradient calculation, non-maximum suppression, and edge tracking by hysteresis. This enhances the precision of tumor delineation, facilitating more accurate diagnosis and effective treatment planning. Histogram adjustment methods, such as Contrast Limited Adaptive Histogram Equalization (CLAHE), further refine the image by enhancing local contrast, making subtle features of the tumor more distinguishable. These combined techniques collectively improve image clarity, aiding in better detection and analysis of brain tumors.

2.4. Convolution

Convolutions are performed using a special kernel to identify features that indicate the presence of a brain tumor, such as abnormal structural patterns and affected areas [40]. In this process, a specific kernel is applied to the image to highlight significant features. For example, the kernel used in this context is:

$$\text{Kernel} = \begin{bmatrix} 0 & 2 & 0 \\ 2 & 5 & 2 \\ 0 & 2 & 0 \end{bmatrix}$$

This kernel is known as a sharpening kernel. It is designed to enhance the contrast of the features by giving higher weights to the central pixels while giving lower weights to the surrounding pixels. By applying this kernel, the convolution process accentuates the prominent features of the tumor and minimizes noise, making structural abnormalities and affected areas more detectable. This helps in identifying and analyzing tumor characteristics with greater accuracy, ultimately supporting more precise diagnosis and treatment planning.

3. Result and Discussion

The results of the proposed imaging processing were evaluated using a collection of brain tumor imaging data from the Brain Tumor dataset contained in Kaggle. The dataset comprises a total of 3,364 images, categorized into four distinct groups: Glioma with 100 image files, Meningioma with 115 image files, No Tumor with 105 image files, and Pituitary Tumor with 74 image files. For this study, images from the Glioma, Meningioma, and Pituitary Tumor categories were specifically utilized. One image file was selected from each of these categories to assess the performance of the proposed image processing techniques. Evaluations were carried out for each step in the process, ranging from image enlargement, pre-processing, and contrast enhancement, to convolutions, to evaluate how each stage affects the quality and usefulness of the diagnostic images of the brain tumors.

3.1. Enlargement

The result of the implementation of image processing algorithms to enlarge the image of the brain is improved resolution successfully clarifies fine details, which are crucial in detecting abnormal structures and small features that mark the presence of brain tumors. The enlarged image shows an increase in pixel density, providing a stronger foundation for the next processing phase. Comparison values for each pixel are presented in Table 1.

Table 1. Pixel Comparison for Each Image

File	Image Before	Image After
Meningioma.jpg	398×351	796×702
Glioma.jpg	453×388	906×776
Pituitri.jpg	400×400	800×800

Table 1 shows changes in image size before and after enlargement in three types of brain tumors: meningioma, glioma, and pituitary. The Meningioma image was initially 398×351 pixels, and after magnification with scale factor 2, it was 796×702 pixels. The Glioma image originally was 453×388 pixels after magnifying to 906×776 pixels; similarly, the pituitary image with an initial size of 400×400 pixels has been magnified to 800×800. This magnification process doubles the image resolution, enabling clearer and more detailed identification of the tumor structure. This enhancement of the resolution is crucial for more accurate diagnosis and better treatment planning, as previously unseen details become clearer.

3.2. Pre-processing

The result of the brain tumor imaging pre-processing phase is that this process helps reduce noise and improve image contrast, preparing images for further analysis and detection phases. This pre-processing is also important to remove potentially disturbing artifacts, such as changes in light intensity or disturbances in MRI images, thus allowing for more accurate tumor detection. In addition, by optimizing the contrast of the image, the important features of the brain tumor can be more clearly seen, improving the physician's diagnostic ability in identifying and assessing the severity of the condition. Overall, this phase is a critical step in the workflow of brain tumor detection, ensuring that the data analyzed is optimal and relevant for medical purposes.

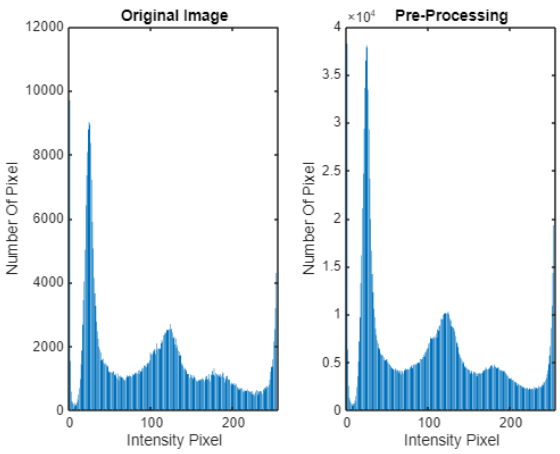

Figure 3. Histogram Before and After Image Processing Meningioma

Figure 3 shows two histograms representing the pixel intensity distribution in the medical picture of meningioma. The first histogram (Original Image) displays the pixel intensity distribution before processing, with peaks and valleys reflecting common and rare intensity values. The second histogram (Pre-Processing) shows the pixel intensity distribution after pre-processing, with the Y axis scaled by (10^4). The main difference between the two histograms is a wider intensity spread and a higher peak on the preprocessed image, showing increased contrast and a clearer separation between different intensity levels.

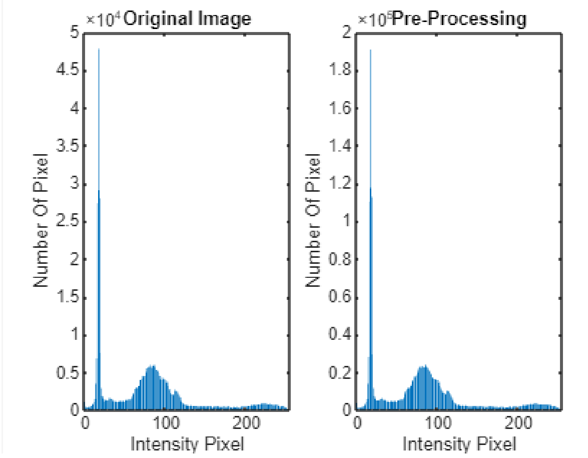

Figure 4. Histogram Before and After Image Processing Glioma

Figure 4 shows two histograms of pixel intensity distribution in the medical picture related to glioma, before and after pre-processing. The first histogram (original picture) shows the pixel intensity distribution with one high peak at a low intensity and several smaller peaks at a higher intensity, with the Y axis scaled by (10^4). The second (pre-processing) histogram shows the distribution of pixels intensity after pre-processing with a higher and clearer peak, especially at low intensities, as well as a more focused intensity spread, with a Y-axis scaled by (10^5). These differences suggest that pre-processing improves image quality by adjusting the pixel intensity distribution, so that features in the image become more easily distinguishable, which is important for more accurate medical analysis and diagnosis.

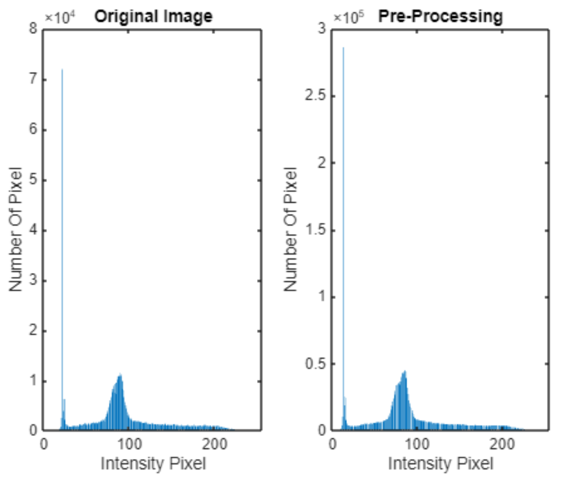

Figure 5. Histogram Before and After Image Processing Pituitri

Figure 4 shows two histograms of pixel intensity distribution in pituitary-related medical images, before and after pre-processing. The first histogram (original picture) shows the pixel intensity distribution with one high peak at a low intensity and a lower spread at a higher intensity, with the Y axis scaled by (10^4). The second Histogram (pre-processing) shows a pixel intense distribution after pre-procesing with a higher and more distinct peak, especially at medium intensities, as well as a more focused intensity spread, with a Y-axis scalled by (10^5). These differences suggest that pre-processing improves image quality by adjusting pixel intensity distribution, reducing dominant low intensity peaks and making features in images more easily distinguishable, which is important for more accurate medical analysis and diagnosis. This pre-processing can also help in better edge detection and image segmentation. With this quality improvement, medical personnel can make more accurate decisions based on a clearer and more informative medical picture.

Table 2. Comparison of Image Correlation Results Before and After Min-Max Filter

File	Before Correlation	After Correlation
Meningioma.jpg	0.9637	0.8382
Glioma.jpg	0.9404	0.8310
Pituitri.jpg	0.9253	0.8234

In Table 2, it can be seen that before processing, the Meningioma image had the highest correlation of 0.9637, which decreased to 0.8382 after processing. These results show that the processing technique has succeeded in reducing the initial high correlations, resulting in a significant improvement in the conformity and quality of the image. Meanwhile, the Glioma image showed a decrease in Correlation from 0.9404 to 0.8310, and the Pituitri image experienced a decrease from 0. 9253 to 0. 8234 after Processing.

3.3. Enhancement

The result of the enhancement phase on the brain tumor image is to strengthen the important features in the image, increase the color difference, and improve the detail of the picture, which helps to prepare the image to be better analyzed and detected further.

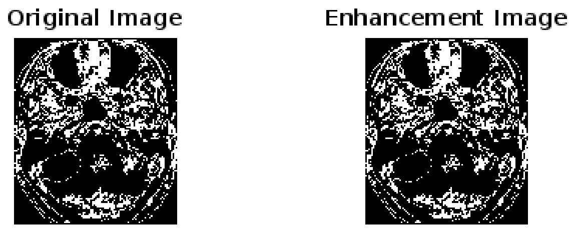

Figure 6. Image Before And After Enhancement Meningioma

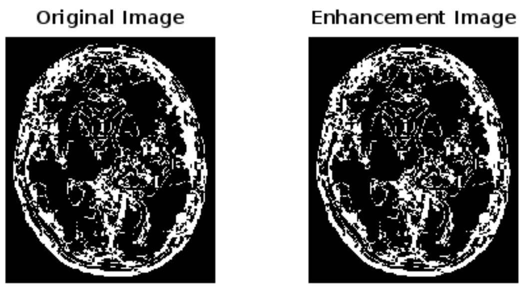

Figure 7. Image Before And After Enhancement Glioma

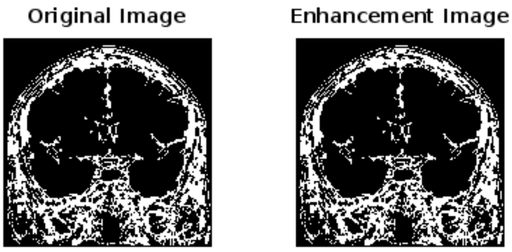

Figure 8. Image Before And After Enhancement Pituitri

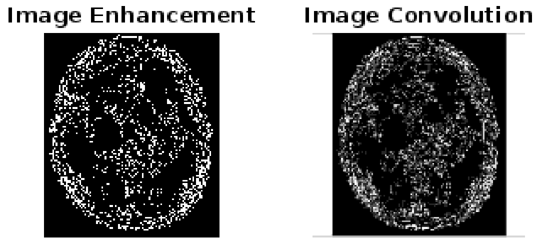

Figure 10. Image Before And After Convolutions Glioma

Figure 6 shows a comparison of the meningioma tumor image before and after enhancement. In Figure 7, the same process is applied to a glioma tumor image, while Figure 8 displays the results before and after enhancement of a pituitary tumor image.

Table 3. Comparison of Image Correlation Results Before and After Enhancement

File	Before Correlation	After Correlation
Meningioma.jpg	0.9637	0.8382
Glioma.jpg	0.9404	0.8310
Pituitri.jpg	0.9253	0.8234

Table 3 shows a comparison of correlation values before and after processing for three types of tumor imaging: Meningioma, Glioma, and Pituitary. From the results obtained, Meningioma images experienced a decrease in correlation from 0.9637 to 0.8382 after processing. This indicates that the processing technique applied successfully reduced the correlation rate by 0.1255, indicating a significant improvement in matching and image quality. Meanwhile, the Glioma image showed a decrease in correlations from 0.9404 to 0.8310 after processing, while the Pituitri image had decreased from 0. 9253 to 0. 8234. Although both images also experienced a decrease in correlation after processing, the increase was not as great as that of Meningioma.

3.4 Convolution

This technique is used to process MRI images of various types of brain tumors, including Meningioma, Glioma, and Pituitary. It is also used to improve the quality and matching of images, as well as to identify important features in the images. Figure 9 shows the meningioma tumor image before and after convolution. Figure 10 displays the same results for a glioma tumor, while Figure 11 presents the convolution results for a pituitary tumor. The results of this convolution analysis were measured using the pre- and post-process correlation values studied in Table 4.

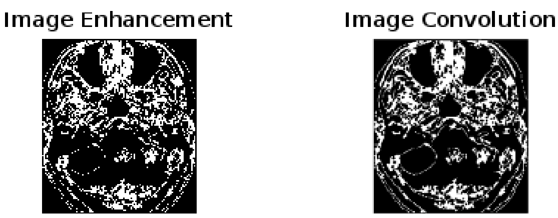

Figure 9. Image Before And After Convolutions Meningioma

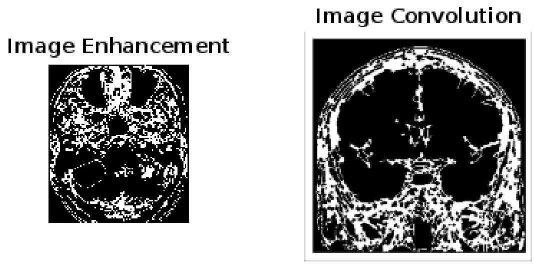

Figure 11. Image Before And After Convolutions Pituitri

Table 4. Comparison of Image Correlation Results Before and After Convolution

File	Before Correlation	After Correlation
Meningioma.jpg	0.9638	0.9851
Glioma.jpg	0.9398	0.9763
Pituitri.jpg	0.9228	0.9886

Based on the results of the convolutions obtained in Table 4, the Pituitri image shows the greatest increase in correlation from 0.9228 to 0.9886, with an increase of 0.0658. This shows that the convolution technique applied is very effective in improving the quality of the Pictuitri picture. Meanwhile, the Glioma image also shows a significant increase from 0.9398 to 0.9763, with an improvement of 0.0365, followed by the Meningioma image which increased from 0.9638 to 0.09851, with an improvement of 0.0213.

3.5 Overall Workflow Performance

The overall workflow performance involving filtering, enhancement, and convolution showed a significant improvement in the quality of brain tumor MRI images. At the filtering stage, disturbing noise was successfully minimized, thereby enhancing the initial clarity of the image. Additionally, the enhancement process strengthened the key features of the image, making it easier to identify and analyze. Finally, the application of the convolution technique resulted in a substantial increase in correlation values across all types of tumors tested, as shown in Table 5.

Table 5. The Whole Result Is Based On Correlation

File	Filtering	Enhancement	Convolution
Meningioma.jpg	0.9851	0.8382	0.9851
Glioma.jpg	0.9763	0.8310	0.9763
Pituitri.jpg	0.9886	0.8234	0.9886

Based on the data in Table 5, the results of this study demonstrate that the Filtering and Convolution methods achieve very high accuracy, with values ranging from 0.98 to 0.99 for detecting meningioma, glioma, and pituitary tumors. These methods have proven to be highly effective in detecting tumors with consistently high accuracy across various image types. In comparison to other methods available in the literature, such as Watershed, Thresholding, K-means, and Edge Detection, the Filtering and Convolution methods show superior detection accuracy. For instance, the Watershed method achieved a tumor area detection of 0.0621 with 3138 pixels and an execution time of 0.366 seconds, whereas the Filtering and Convolution methods provided significantly higher detection accuracy.

Therefore, this study underscores the importance of utilizing image processing techniques that enhance detection accuracy without compromising execution time. Based on these findings, the Filtering and Convolution methods employed in this study are superior in terms of detection accuracy and result consistency, while also preserving image clarity, which is crucial for the effective identification and analysis of tumor structures.

4. Conclusion

From the analysis of brain tumor imaging using filtering, enhancement, and convolution techniques, it appears that filtering and convolution techniques yield similar and optimal results for Meningioma.jpg and Pituitri.jpg images, with high correlation values of 0.9851 and 0.9886 in succession. It shows the effectiveness of the technique in improving the clarity and quality of the image, preparing the image for more accurate analysis and diagnosis. On the other hand, although enhancements also provide significant contrast improvements, slightly lower correlation values on all images suggest that this technique may be more useful as a support in clarifying important structural details in brain tumor MRI images. Overall, the combination of filtering and convolution techniques proves that it is important in image processing to support better diagnosis and treatment planning for patients with brain tumors.

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