VISVESVARAYA TECHNOLOGICAL UNIVERSITY
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A Project Report
on

"Multimodal Medical Imaging for the Detection and Analysis of Brain Tumors"

Submitted in partial fulfilment of the requirements for the award of

BACHELOR OF ENGINEERING
in
ELECTRONICS AND COMMUNICATION ENGINEERING

by

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CERTIFICATE

Certified that the project work entitled **"Multimodal Medical Imaging for the Detection and Analysis of Brain Tumors"** is a bonafide work carried out by **Amrutha K M , Gangotri H S, Sucheta Krishna Naik,** bearing USN's **4SH21EC001, 4SH21EC003, 4SH21EC011** respectively in partial fulfilment for the VTU CBCS subject **Project**, and for the award of degree of **Bachelor of Engineering** in **Electronics and Communication** of the Visvesvaraya Technological University, Belagavi during the year 2024-2025. It is certified that all corrections / suggestions indicated for Internal Assessment have been incorporated in the report deposited in the departmental library. The project report has been approved as it satisfies the academic requirements in respect of project work prescribed for the degree of Bachelor of Engineering.

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DECLARATION

We **Amrutha K M** , **Gangotri H S, Sucheta Krishna Naik,** bearing USN's **4SH21EC001, 4SH21EC003, 4SH21EC011** respectively, students of 7th semester Bachelor of Engineering, Electronics and Communication, Shree Devi Institute of Technology, Mangalore declare that the project work entitled **"Multimodal Medical Imaging for the Detection and Analysis of Brain Tumors"** has been duly executed by us under the guidance of **Mrs. Nischitha**, Asst. Professor, Department of Electronics and Communication Engineering, Shree Devi Institute of Technology, Mangalore and submitted for the requirements for the 7th semester **Project** of **Bachelor of Engineering** in **Electronics and Communication** during the year 2024-2025.

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ABSTRACT

Medical imaging plays a vital role in disease diagnosis and treatment. However, individual imaging modalities (e.g., MRI, CT, PET) often provide limited information, leading to diagnostic uncertainties. Multimodal image fusion aims to combine the complementary information from different modalities to produce a single, more informative image. This project proposes a novel multimodal image fusion framework for medical image processing. This approach leverages advanced techniques in image registration, feature extraction, and fusion to combine the strengths of different modalities. The proposed framework is evaluated on a dataset of multimodal medical images (MRI, CT, PET) for various clinical applications. Experimental results demonstrate the effectiveness of this approach in enhancing diagnostic accuracy, improving image quality, and providing more comprehensive information for clinical decision-making.

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CHAPTER 1

INTRODUCTION

Medical imaging for the detection and analysis of brain tumors leverages the strengths of combining Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) to provide a comprehensive view of tumor characteristics. MRI excels in highlighting soft tissue contrasts, aiding in precise tumor localization, while CT provides detailed information on bone structures and calcifications. By fusing these complementary modalities, medical professionals can enhance diagnostic accuracy, improve treatment planning, and gain deeper insights into tumor size, shape, and location, ultimately leading to better clinical outcomes. Advanced techniques such as image fusion algorithms further optimize the integration of MRI and CT data for superior visualization.

1.1 IMAGE PROCESSING

Recent technological advancements have sparked increased interest in image processing techniques, especially within the realm of medical image analysis. Image processing has emerged as a vital research area in Engineering and Computing, driving the development of methods to enhance image quality and extract valuable information for diagnostic purposes. In this project, image processing serves as a fundamental tool to improve the clarity of medical images, enabling better detection and analysis of brain tumors. The technique involves transforming raw image data into a digital format, applying a series of operations to refine the image, and ultimately preparing it for accurate interpretation. These operations help enhance the image's characteristics and make it more suitable for further analysis.

The image processing workflow in this project consists of multiple stages, such as image preprocessing, enhancement, and feature extraction. Initially, raw images undergo preprocessing to standardize their size, normalize intensity values, and convert them into a uniform format. Once processed, the images are further enhanced to improve their clarity and highlight significant features, making it easier to detect tumors or other anomalies. In the context of medical imaging, these images are often in grayscale, where pixel values correspond to light intensity levels, ranging from dark shades for low intensity to bright shades for higher intensity. The project applies image processing techniques to ensure the images are optimized for precise and reliable analysis, facilitating more accurate diagnosis and treatment planning. By improving the overall quality of the medical images, the project enables more effective tumor detection and aids in the extraction of crucial information for medical professionals[4].

1.2 IMAGE FUSION

Image fusion is a critical technique in digital image processing that has found widespread use in various scientific and technological fields, especially in medical image analysis. The process of image fusion involves the combination of information from two or more input images to generate a single output image. This output image typically contains more detailed, accurate, and informative data than any of the individual input images, which is crucial for precise diagnosis and treatment planning. In the context of medical imaging, such as in brain tumor detection, image fusion plays an essential role in enhancing the quality of diagnostic images, enabling healthcare professionals to make more informed decisions.

In this project, image fusion is used to merge medical images, such as those acquired through different modalities, into one comprehensive image. These input images may vary in terms of their source, such as multi-sensor, multimodal, multifocal, or multi-temporal images. Each modality or sensor offers distinct advantages, and by combining the information from these images, image fusion ensures that the fused image contains a more complete set of features. For example, in brain tumor detection, a combination of images from different modalities like CT and MRI could be used to generate an image that incorporates both the structural and functional details of the brain, offering a more holistic view of the tumor's size, location, and characteristics.

One of the most widely used methods in image fusion is wavelet theory, which allows for the decomposition of an image into various frequency bands (low and high frequency). These bands can then be processed separately to enhance certain features in the image. The fusion process in this project employs wavelet theory to combine different levels of image information from the input images into a unified output. The high-frequency bands, which contain fine details such as edges and textures, are particularly important for tumor detection, as they help to preserve sharp features that are crucial for identifying boundaries and anomalies. The low-frequency bands, on the other hand, contain the general structure of the image, ensuring that the overall content is preserved and that the fused image maintains its contextual integrity.

Image fusion serves a wide range of applications, extending beyond medical imaging into fields such as remote sensing, ocean surveillance, and artificial neural networks. In each of these areas, the ability to combine multiple sources of information into a single, more informative image is invaluable. In remote sensing, for example, image fusion helps to combine data from different satellite sensors to create clearer, more detailed maps of the Earth's surface. Similarly, in ocean surveillance, multiple image sources can be fused to track environmental changes or monitor marine life. In artificial neural networks, image fusion is used to improve the quality of input data, leading to better performance of machine learning models in tasks such as object recognition and classification.

In medical imaging, the need for image fusion is particularly pronounced due to the complexity of the human body and the limitations of individual imaging modalities. CT scans and MRI scans, for instance, provide complementary information about the structure and function of the body. While CT scans are excellent for providing detailed images of bones and soft tissues, MRI scans excel at capturing detailed images of soft tissue structures like the brain. By combining these two modalities, image fusion can create an image that provides both the anatomical and functional details needed for accurate diagnosis and treatment planning. This is especially important in the detection and analysis of brain tumors, where both the location and size of the tumor are critical for determining the appropriate course of action.

Image enhancement is another critical aspect of the image fusion process. The primary goal of image enhancement is to improve the quality of the image to make it more suitable for human interpretation and machine analysis. In the context of this project, image enhancement techniques are applied to the fused image to ensure that it is clear, high-quality, and informative. These techniques can include contrast adjustment, noise reduction, and sharpening, all of which contribute to making the fused image more visually interpretable and suitable for automated analysis by algorithms. The resulting enhanced image is not only easier to analyse for medical professionals but also provides a more accurate representation of the structures within the body, such as the brain tumor.

The process of image fusion involves several key steps. Initially, the images to be fused are pre-processed to standardize their format, resolution, and size. This ensures that the images are aligned and that the fusion process can be carried out efficiently. After preprocessing, the images are decomposed into their respective frequency bands using techniques like wavelet transformation. Next, fusion rules are applied to combine the information from each band, with different strategies used for high-frequency and low-frequency bands. For instance, the high-frequency bands are typically fused using maximum selection rules to preserve sharp features, while the low-frequency bands are combined using averaging techniques to ensure smooth transitions between the images. Finally, the fused image is reconstructed using inverse wavelet transformation, resulting in a high-quality output image.

Once the fused image is generated, it is evaluated using various quality metrics to assess its performance. Common quality metrics include entropy, which measures the amount of information contained in the image, standard deviation, which indicates the contrast of the image, and mutual information, which assesses the amount of shared information between the input images and the fused image. These metrics are essential for ensuring that the fused image is not only visually clear but also contains meaningful information that can be used for further analysis.

The image fusion is an essential technique in medical image processing, particularly in the detection and analysis of brain tumors. By combining information from multiple image modalities, the fusion process enhances the clarity and detail of medical images, leading to more accurate diagnoses and better-informed treatment plans. The use of wavelet theory and image enhancement techniques further improves the quality of the fused images, making them more suitable for both human interpretation and machine analysis. The ability to fuse and enhance images from various sources provides a comprehensive view of the body, facilitating the detection of tumors and other anomalies with greater precision. The success of image fusion in medical imaging demonstrates its value in advancing diagnostic capabilities and improving patient care.

This project aims to develop an advanced system for brain tumor detection and analysis using image processing techniques. By utilizing image fusion methods, it combines data from multiple imaging modalities, such as CT and MRI scans, to generate a single, enhanced image that provides detailed insights into brain structures. The project focuses on improving the clarity and visibility of tumor details through image enhancement techniques, including contrast adjustment, noise reduction, and sharpening. The goal is to create accurate, informative fused images that support better diagnostic and treatment planning, ultimately aiding healthcare professionals in making more informed decisions.

CHAPTER 2

LITERATURE SURVEY

Molham Moshantat et. al. [1], in their proposed work medical image fusion plays a crucial role in enhancing disease diagnosis and treatment planning by combining complementary information from different modalities like CT and MRI. CT provides structural data, while MRI offers detailed tissue information, but individually, lack of clarity for effective analysis. By using discrete wavelet transform (DWT) with wavelets such as Haar, Daubechies, Mexican Hat, Symlets, Morlet, and Shannon, fused images can integrate essential features from both modalities, improving diagnosis accuracy. DWT-based fusion enhances metrics like PSNR and entropy, ensuring high-quality outputs for medical applications. This process is vital for extracting precise, complementary data for better disease analysis.

M. Sajeer et. al. [2], in their proposed work digital image watermarking has gained significant attention in recent years, particularly in medical imaging, where data authentication and integrity are critical. Recent advancements have integrated image fusion to enhance image quality and improve diagnostic accuracy. For this project, image processing techniques such as wavelet transforms and fusion methods have been explored to combine multimodal medical images effectively. These fused images provide enriched details for precise brain tumor detection and analysis. The approach focuses on leveraging advanced algorithms like wavelet-based fusion and feature extraction techniques to generate an enhanced single image from multiple inputs. This fused image facilitates accurate analysis, aiming to enhance the reliability of tumor detection in medical imaging. By applying cutting-edge image processing methodologies, project builds upon existing research to deliver a robust and scalable solution tailored for medical applications.

Jaskeerat Kaur et.al. [3], in their proposed work wavelet-based techniques such as DWT and DCT play a critical role in enhancing image fusion by improving sharpness, accuracy, and informativeness. Image fusion combines essential information from multiple input images into a single output image that is completer and more useful for various applications, including medical imaging, robotics, remote sensing, and computer vision. These techniques ensure high-quality fused images that benefit both human vision and machine perception, enabling effective real-world information extraction. While wavelet methods offer significant advantages, they also require careful evaluation to address potential limitations. Researchers can explore these methods to refine image fusion processes for diverse scientific fields. DWT, in particular, facilitates multi-resolution analysis, making it a key approach in achieving enriched and application-ready images. By addressing the limitations of individual input images, wavelet-based fusion ensures enhanced accuracy and completeness, which is essential for future image-processing tasks and advancements across various domains.

Gerald K et. al. [4], according to their proposed work recent advancements in MATLAB-based analytics have revolutionized image processing by offering efficient tools for operations like cropping, resizing, denoising, blur removal, and sharpening. Compared to traditional methods, MATLAB provides advantages such as easy debugging, concise code, and extensive data visualization. Its capability to handle errors before execution and optimize code performance makes it highly effective for both still and video image processing. MATLAB-based simulations, using techniques like two- dimensional discrete cosine transform (2D-DCT), enhance computational efficiency and accuracy. The study highlights MATLAB as a powerful platform for implementing and testing advanced algorithms for improved image processing outcomes.

Xin Jin et. al. [5], in their proposed work computational imaging has become a critical tool in the field of medical diagnostics, offering comprehensive insights into human tissue for effective diagnosis and treatment. Medical image fusion is one of the most vital techniques in this domain, enabling the combination of critical information from multiple modalities into a single, enriched image. While methods such as Empirical Mode Decomposition (EMD) have been previously explored, challenges like inconsistent decomposition layers limit their utility. In this project, advanced image fusion techniques are employed to enhance medical imaging analysis. By leveraging wavelet-based decomposition methods, the proposed approach extracts critical features from multimodal images and combines them into a detailed and informative output. This ensures the integration of vital details necessary for accurate tumor detection and analysis. The project adopts robust computational imaging methodologies to optimize feature extraction and fusion processes, providing an innovative solution that builds upon existing technologies for better precision and usability in medical imaging applications.

Kedar Nath Singh et. al. [6], according to their proposed approach the exponential growth of big data in medical applications has brought significant opportunities and challenges, particularly in securely sharing sensitive medical images. Ensuring the protection of such data during storage and transmission has become even more critical post-pandemic. Recent advancements in medical image processing highlight the use of secure algorithms for enhancing data integrity and privacy. For instance, methods like encryption, watermarking, and multimodal image fusion have been employed to address security concerns while maintaining diagnostic accuracy. In this project, a novel approach is adopted to achieve secure and robust medical image fusion. Using advanced wavelet decomposition techniques combined with efficient feature extraction methods, the system integrates critical details from multiple images while ensuring data privacy and security. These technologies optimize invisibility and robustness, reinforcing the reliability of the medical data for diagnostic and research purposes, without compromising its integrity or authenticity during transfer.

M. D. Nandeesh et. al. [7], in their proposed work Medical imaging modalities like CT and MRI provide complementary data for accurate diagnosis. Image fusion enhances diagnostic precision by retaining essential details and eliminating redundancies. Preprocessing steps such as skull stripping and Affine transformation ensure proper image alignment before fusion. Techniques like Principal Component Analysis (PCA), Discrete Curvelet Transform (DCVT), and Stationary Wavelet Transform (SWT) are widely used for medical image fusion. Hybrid approaches combining PCA with DCVT and PCA with SWT improve fusion performance. These methods enhance contrast, clarity, and feature retention, aiding in better tumor detection. Various performance evaluation techniques assess the effectiveness of fusion methods based on structural similarity and clarity. The fused images assist radiologists in detecting brain tumors with greater accuracy. Hybrid techniques outperform traditional methods, proving their reliability in medical imaging. Future research can explore deep learning-based fusion for further improvements in tumor detection.

M. Poshitha et. al. [8], the proposed work as described that glioma, the most common primary brain tumor, arises from glial cell carcinogenesis in the central nervous system. Accurate tumor localization and segmentation from MRI images remain critical for healthcare evaluation. Modern methods utilize multimodal imaging, including T1, T1c, T2, and FLAIR, to capture comprehensive tumor characteristics. Reliable tumor segmentation is essential for diagnosis, treatment planning, and patient survival prediction. A fuzzy-based system leveraging multimodal MRI images enhances tumor classification and glioma survival estimation. To improve Fuzzy C-means (FCM), a weighted function is integrated, addressing its limitations. Extensive testing on BRATS datasets confirms the competitive performance of Weighted FCM (WFCM). Comparison with ground truth images validates the segmentation accuracy. Performance metrics assess both qualitative and quantitative results. The extracted tumor regions aid medical professionals in early diagnosis and treatment planning.

E. Kannan et. al. [9], in their proposed work address the low accuracy of traditional brain tumor detection, a multimodal information fusion method combined with convolutional neural networks (Multi-CNNs) was proposed. The addition of a real normalization layer improves convergence speed and reduces overfitting, while a weighted loss function enhances feature learning in lesion areas. The proposed architecture leverages complementary information from multiple imaging modalities, including T1, T2, and FLAIR sequences, to provide a more comprehensive tumor characterization. Experimental results demonstrate significant improvements in tumor localization and detection accuracy, achieving better sensitivity, specificity, and correlation coefficients compared to single-modal or 2D detection networks. The method shows particular promise in detecting tumor boundaries and distinguishing between different types of brain tissue abnormalities. The computational efficiency of the proposed approach was also evaluated, with the multi-modal fusion and 3D-CNN architecture requiring only minimal additional processing time compared to traditional methods while delivering substantially improved diagnostic reliability. This makes the system particularly suitable for clinical implementation where both accuracy and timeliness are critical factors.

Ankur et. al. [10], in thier proposed brain tumor detection is crucial for effective treatment, as stress and challenges in daily life can contribute to severe health issues. Convolutional Neural Networks (CNNs) have proven effective in medical image analysis, particularly for tumor detection. However, their performance is often constrained by the limited availability of annotated medical images. A comprehensive review of research databases like Scopus, Web of Science, and IEEE Explore identified 20 full-text articles from 674 abstracts. Various ResNet models, including ResNet-50, ResNet-101, and ResNet-152, have been evaluated for their diagnostic accuracy. Key performance metrics such as sensitivity, specificity, F1-score, and AUC highlight the superiority of ResNet over traditional machine learning approaches. ResNet-based methods exhibit enhanced robustness in detecting brain tumors. However, challenges persist in integrating multimodal imaging data and ensuring model generalization. Despite these issues, ResNet-50 has demonstrated promise in systematic and noninvasive neuroimage analysis. Future advancements can further refine deep learning-based tumor detection techniques.

M. Fan et. al. [11], in this proposed work, computer image enhancement processing, learning and analysis were carried out on a large number of brain multimodal medical images

(MRI) from patients and a deep convolutional neural network was established to generalize the mask mapping function paradigm of learning images and diseased areas, so as to achieve accurate classification of high-grade glioma (HGG) and low-grade glioma (LGG); the semantic segmentation whole tumor area (WT) was carried out.

M. Meenakshi et. al. [12], in their proposed work Brain tumor detection is crucial for accurate diagnosis and treatment planning, with medical imaging techniques like CT and MRI playing a key role. These non-invasive modalities assist in identifying suspicious tumor regions, but a single modality may not provide comprehensive details. To enhance diagnostic accuracy, hybrid image fusion techniques combining Principal Component Analysis (PCA) and Stationary Wavelet Transform (SWT) integrate complementary and redundant information. The fused image offers a more detailed representation, aiding in precise tumor localization. Enhanced Fuzzy C-Means (EFCM) clustering is utilized for segmentation, effectively extracting tumor regions. The fusion process improves segmentation accuracy by providing enriched information. EFCM enhances traditional FCM by leveraging fused image data, leading to superior tumor detection. Performance evaluation confirms the effectiveness of both fusion and segmentation techniques. The proposed approach results in better-quality images for improved medical analysis. Future advancements can further refine segmentation and fusion methods for enhanced tumor detection.

Rui Zhu et. al. [13], in their proposed work Medical image fusion integrates critical information from multi-modality images like MRI and CT into a single, highly informative image that enhances diagnostic accuracy and clinical decision-making. The proposed method employs an advanced Synchronized- Anisotropic Diffusion Equation (S-ADE) model to efficiently decompose source images into base and texture layers, separating structural and detailed information. Fusion techniques are carefully designed to optimize the integration process: the "Maximum Absolute Value" rule is applied to base layers, ensuring that key structural features are retained, while the NSMAL (Non-Subsampled Morphological Adaptive Laplacian) algorithm is used to process texture layers, preserving high-frequency details and enhancing the clarity of pathological features. To ensure consistency, a consistency verification mechanism is incorporated to minimize artifacts like staircase effects, which often degrade image quality. Finally, a precise linear combination is used to reconstruct the fused image, maintaining a balance between enhanced clarity and reduced redundancy.

CHAPTER 3

PROBLEM STATEMENT

Brain tumors, such as Glioblastoma (GBM) and Meningioma, present significant challenges in medical diagnosis and treatment. These tumors are highly complex and often aggressive, requiring precise and timely diagnostic techniques to ensure effective clinical management. Currently, imaging modalities like Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and Positron Emission Tomography (PET) are the most commonly employed diagnostic tools. Each of these imaging techniques provides unique insights into the brain's structure and function. For example, CT scans excel in capturing bony structures and calcifications, MRI provides high-resolution details of soft tissues, and PET highlights metabolic activity. However, when used individually, these modalities fail to provide a comprehensive picture, as each focuses on distinct aspects of the tumor and may miss critical information present in other modalities.

In practice, the reliance on a single imaging modality can lead to diagnostic uncertainties. For instance, certain features of brain tumors that are evident in one modality might be obscured or entirely absent in another. As a result, clinicians may face challenges in accurately identifying tumor boundaries, assessing tumor progression, or determining the efficacy of therapeutic interventions. To address this issue, multimodal image fusion has emerged as a promising approach. By combining information from multiple imaging modalities into a single fused image, this technique enables clinicians to access a more holistic and detailed view of the brain, improving the accuracy of diagnosis and decision-making.

Despite its potential, existing image fusion techniques are often limited by several shortcomings. Conventional methods may suffer from information loss, reduced contrast, high levels of noise, or the inability to preserve critical features from the source images. These limitations can lead to suboptimal image quality, reducing the clinical utility of the fused images. Furthermore, the high computational cost and complexity of some fusion algorithms can hinder their practical implementation in real-world medical settings.

To overcome these challenges, this project aims to develop a robust and efficient MATLAB-based multimodal image fusion framework specifically designed for brain tumor diagnosis. The proposed framework will leverage Modified Singular Value

Decomposition (MSVD) and Discrete Wavelet Transform (DWT), two advanced mathematical techniques known for their capability to effectively process and preserve image features. MSVD is well-suited for enhancing structural details and preserving global image information, while DWT excels at capturing localized features and minimizing noise. The ultimate goal of this project is to provide a reliable, efficient, and clinically applicable image fusion framework that can assist healthcare professionals in diagnosing Glioblastoma and Meningioma with greater accuracy. By enhancing the quality and utility of fused images, this solution will contribute to improved clinical decision-making and better patient outcomes. This framework has the potential to bridge the gap between imaging technology and clinical needs, addressing the limitations of existing methods and paving the way for advancements in brain tumor diagnosis.

DWT is a signal processing technique that decomposes an image into different frequency components using wavelet functions, capturing both spatial and frequency information. It works by dividing the image into approximation (low- frequency) and detail (high-frequency) sub-bands, enabling efficient feature extraction and reconstruction for tasks like image fusion. MSVD is an advanced extension of Singular Value Decomposition (SVD) that decomposes a matrix into three components singular values, left singular vectors, and right singular vectors—allowing for efficient representation and manipulation of data. In image fusion, MSVD enhances critical features by adjusting singular values to emphasize significant details while suppressing less relevant information, ensuring high-quality fused images.

This project utilizes two techniques DWT and MSVD. DWT is a signal processing technique that decomposes an image into different frequency components using wavelet functions, capturing both spatial and frequency information. MSVD is an advanced extension of SVD that decomposes a matrix into three components singular values, left singular vectors, and right singular vectors allowing for efficient representation and manipulation of data.

CHAPTER 4

PROPOSED METHODOLOGY

The proposed methodology enhances the quality of brain tumor detection by utilizing multimodal imaging techniques like MRI, CT, and PET to capture complementary tumor details. Preprocessing improves image clarity through noise reduction and normalization, followed by segmentation to isolate tumor regions. Feature extraction methods such as DWT and MSVD analyze entropy and texture for better characterization.

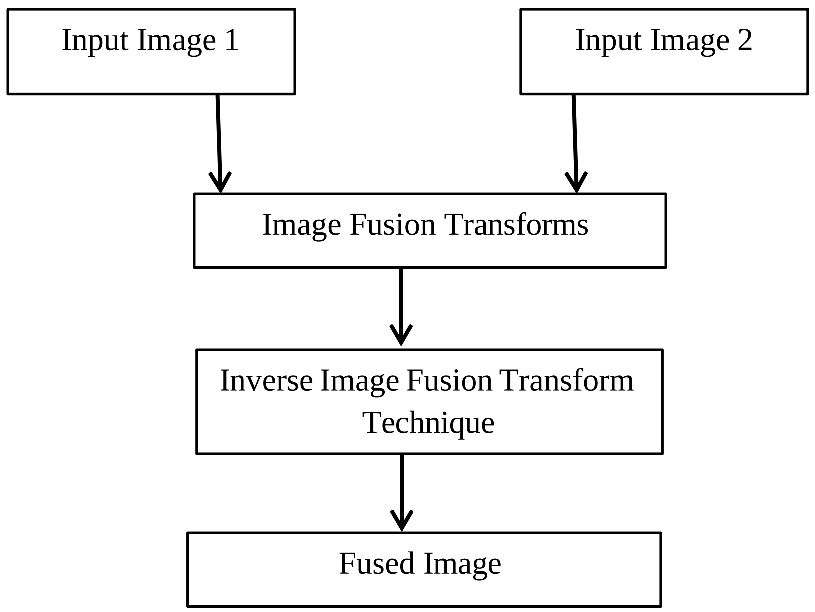


Figure 4.1: Overview of the proposed work

The Figure 4.1 represents an image fusion process, where two input images are combined to create a single enhanced image. Initially, Input Image 1 and Input Image 2 undergo image fusion transforms, which apply transformation techniques like Discrete Wavelet Transform (DWT), Multi-Scale Singular Value Decomposition (MSVD) to extract features. The transformed images are then processed through inverse image fusion transforms, which reconstruct the fused image by integrating relevant details from both inputs. The final output is a fused image, which retains the most significant features from both input images, enhancing visual quality and information content for improved medical analysis or other applications.

4.1 WAVELET TRANSFORM

Wavelet Transform (WT) is a mathematical technique used to analyze signals by decomposing them into different frequency components while preserving time information. Unlike the Fourier Transform, which only provides frequency domain representation, the Wavelet Transform offers a multi-resolution analysis, allowing signals to be studied at various scales. It is particularly useful for analyzing non-stationary signals, where frequency components change over time.

The Wavelet Transform works by using small wave-like functions called wavelets, which are scaled and shifted versions of a mother wavelet. These wavelets can capture both high-frequency details and low-frequency trends in a signal, making WT highly effective for detecting sudden changes, such as edges in images or anomalies in signals. The process involves convolving the signal with wavelets at different scales, providing detailed insights into signal characteristics across different time intervals.

One of the key advantages of the Wavelet Transform is its ability to represent signals in both time and frequency domains simultaneously. This dual representation is crucial in fields such as signal processing, image compression, and machine learning, where analyzing patterns at multiple resolutions is necessary. By efficiently breaking down complex signals into simpler components, the Wavelet Transform enables advanced techniques for filtering, compression, and feature extraction, making it an essential tool in modern data analysis.

4.1.1 Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform (DWT) is a mathematical tool used for analyzing signals by breaking them down into different frequency components while maintaining time localization. It is based on the principle of decomposing a signal into approximation and detail coefficients, which helps in extracting relevant information from the data. DWT is widely used due to its computational efficiency and ability to analyze signals at multiple resolutions.

DWT operates by applying discrete filtering and down-sampling techniques. The signal is passed through a low-pass filter to extract approximation coefficients, which capture the overall trend, and a high-pass filter to extract detail coefficients, which preserve finer variations. This process can be repeated multiple times to obtain a hierarchical decomposition, allowing better representation of the signal at different scales.

One of the major characteristics of DWT is its multi-resolution analysis (MRA), which enables signal representation at different levels of granularity. By decomposing a signal into different frequency bands, DWT allows for a more precise understanding of variations in data. This hierarchical approach helps in identifying important features while reducing redundancy, making DWT an efficient method for processing signals.

DWT ensures efficient data representation by reducing the number of coefficients required to describe a signal while preserving essential information. It provides a compact and structured form of data, making it suitable for applications that require high computational efficiency. The ability of DWT to separate significant signal components from irrelevant noise further enhances its usefulness in various fields.

In conclusion, the Discrete Wavelet Transform is a highly effective technique for analyzing signals due to its structured decomposition and multi-resolution capabilities. By efficiently representing data in different frequency components, DWT provides an optimal balance between accuracy and computational efficiency.

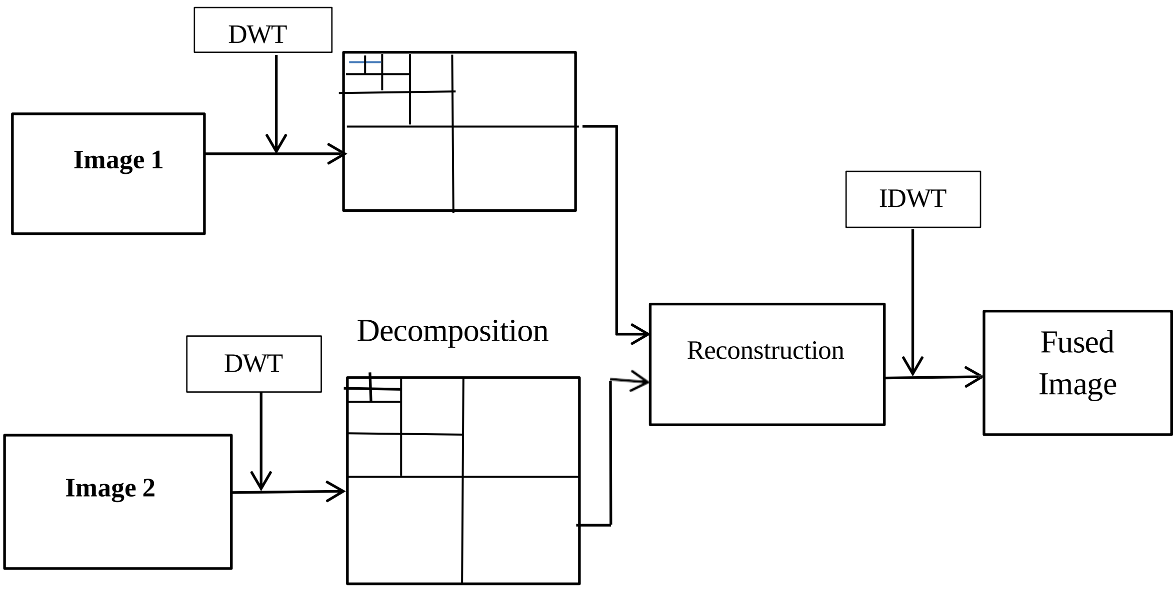


Figure 4.2 DWT-Based Image Fusion Process [3]

The Figure 4.2 represents a DWT (Discrete Wavelet Transform)-based Image Fusion Process, which is commonly used in medical imaging, remote sensing, and other image processing applications. This process consists of several stages:

Source Images:

The process begins with two input images (Image 1 and Image 2). These images may come from different modalities (e.g., CT and MRI scans) or different conditions. The goal is to extract and combine the most relevant information from both images to create a fused image with enhanced features.

Decomposition using DWT:

Each input image undergoes DWT decomposition. DWT breaks down the images into multiple frequency sub-bands, separating low-frequency (approximate details) and high-frequency (edge and texture details) components. This decomposition helps in analyzing the most significant features of each image.

Feature Selection and Fusion:

Once the images are decomposed, specific rules are applied to select the most relevant features from both images. Generally, the low-frequency components retain structural information, while high-frequency components preserve edge and texture details. The fusion rule determines how these components are combined to form a new, enhanced representation.

Reconstruction using IDWT:

After feature selection, an Inverse Discrete Wavelet Transform (IDWT) is applied to reconstruct the image from the selected frequency components. This step ensures that the fused image retains the best aspects of both input images while minimizing noise and distortion.

Final Fused Image:

The final output is a Fused Image, which combines useful details from both input images into a single, more informative image. This fused image enhances visibility, improves feature representation, and is beneficial in applications like medical diagnostics, surveillance, and image enhancement.

4.2 MULTI-RESOLUTION SINGULAR VALUE DECOMPOSITION (MSVD)

Multi-resolution Singular Value Decomposition (MSVD) is an extension of traditional Singular Value Decomposition (SVD), applied to image processing for enhancing data analysis and compression techniques. In image processing, images are often represented as matrices where each pixel corresponds to an element in the matrix. SVD decomposes the image matrix into three components: U (left singular vectors), Σ (singular values), and V (right singular vectors). However, in MSVD, this process is extended to multiple resolutions or scales, allowing the decomposition of images at varying levels of detail. This approach helps capture both global and local features in an image, which is especially useful when dealing with high-resolution images or when attempting to compress them effectively.

The concept behind MSVD is to apply SVD iteratively on different scales of an image. Each scale or resolution represents a version of the image with varying levels of detail, typically starting from the highest resolution (full image) and progressively down to lower resolutions (coarse versions of the image). By decomposing the image at multiple resolutions, MSVD enables the analysis of features that might only be visible at specific levels of detail. For instance, fine textures and edges may only appear clearly at a higher resolution, while broader structures or patterns become more prominent at lower resolutions.

By working on a multi-resolution scale, MSVD reduces the computational load associated with processing high-resolution images. For instance, when working on image compression, MSVD can focus on the dominant singular values at lower resolutions, while refining the image representation at higher resolutions. This hierarchical approach allows for better compression rates with minimal loss of important details, which is critical in applications like image storage and transmission, where bandwidth and memory are limited.

Multiscale Singular Value Decomposition (MSVD) applies Singular Value Decomposition (SVD) iteratively across different image resolutions, enabling a hierarchical analysis of image features. At higher resolutions, fine textures and edges become more distinct, while broader patterns emerge at lower resolutions. This multi-resolution approach not only enhances feature extraction but also reduces computational overhead.

Multi-resolution Singular Value Decomposition enhances the capabilities of traditional SVD by enabling the analysis of images at various levels of resolution. This approach is highly beneficial for image compression, feature extraction, and recognition, especially when dealing with large datasets or requiring efficient processing. By breaking down the image into multiple scales, MSVD captures both global and local features, leading to improved performance in a variety of image processing tasks.

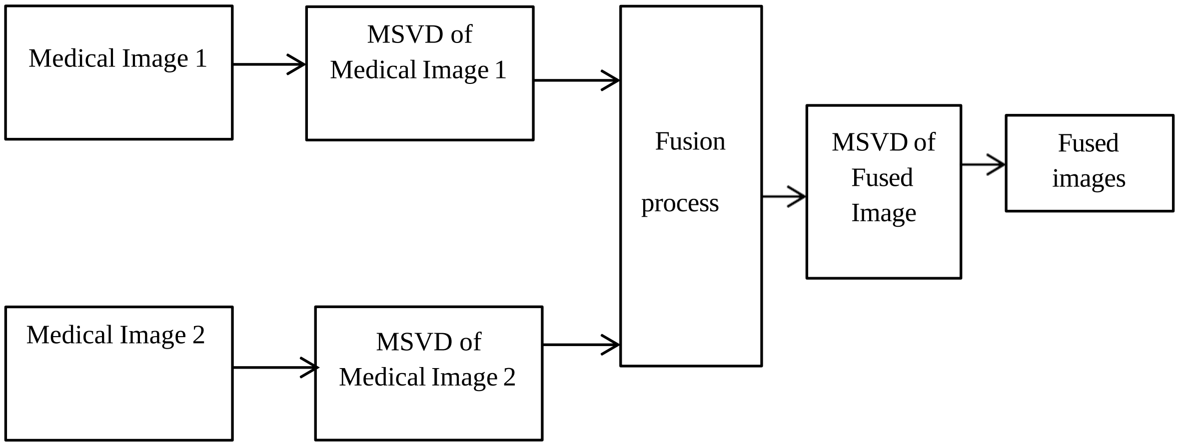


Figure 4.3 MSVD-Based Medical Image Fusion [14]

The figure 4.3 represents an MSVD (Multi-resolution Singular Value Decomposition) based medical image fusion process. It illustrates how two medical images from different imaging modalities (such as MRI, CT, or PET scans) are first decomposed using MSVD. The decomposed components are then fused through a fusion process, followed by applying inverse MSVD again on the fused image to enhance its quality. The final output is a fused image that combines relevant structural and functional details from both input images, aiding in better medical analysis, such as brain tumor detection.

Medical Image 1 & Medical Image 2:

These are the input images taken from different imaging modalities (e.g., MRI, CT, PET scans) for brain tumor detection and analysis. Each image provides unique information about the brain's structure and abnormalities.

MSVD of Medical Image 1 & MSVD of Medical Image 2:

Scale Singular Value Decomposition (MSVD) is applied to each medical image. MSVD helps in decomposing the images into multiple scales and extracts significant features such as intensity variations and edge details, which are essential for accurate image fusion.

Fusion Process:

This is the core step where the key features from both medical images (obtained via MSVD) are combined. The fusion process ensures that the most relevant details from each image are integrated, resulting in an enhanced and more informative image that highlights critical medical information.

MSVD of Fused Image:

After fusion, MSVD is applied again to the fused image to refine and enhance the features further. This step ensures that the fused image maintains clarity, retains important structures, and removes redundant or less significant details.

Fused Images:

This is the final output, where a single, high-quality fused image is generated. The fused image provides a comprehensive view, combining crucial details from both input images. This aids medical professionals in better diagnosis and analysis of brain tumors, improving accuracy and decision-making.

CHAPTER 5

PERFORMANCE METRICS FOR IMAGE FUSION

Performance metrics for image fusion evaluate the quality and effectiveness of the fused image. Mean (μ) measures the average intensity, indicating the brightness level of the image. Entropy (H) quantifies the amount of information or randomness in the image, where higher entropy signifies better feature retention. Standard Deviation (σ) represents the contrast and variation in pixel intensities, with a higher value indicating better edge and texture preservation. Mutual Information (MI) (ma, mb) assesses the shared information between the fused image and the original images, where higher MI values suggest better fusion performance. Fusion Factor (FF) evaluates the balance between source images and the fused image, ensuring an optimal combination of features from both inputs.

5.1 MEAN (μ)

Mean in image fusion represents the average intensity of an image, which helps in understanding its overall brightness. It is an important metric as it indicates how well the fused image maintains the intensity distribution of the source images. A higher mean value suggests that the image is brighter, while a lower mean indicates a darker image. In the context of image fusion, the mean should ideally preserve the significant intensity details from both input images to ensure that no critical information is lost.

The mean is calculated using the formula:

$$\mu = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} I(i,\ j) \qquad (5.1)$$

Where:

M and N are the dimensions of the image (number of rows and columns).

$I(i, j)$ represents the intensity value at each pixel (i, j).

The mean intensity of a fused image plays a crucial role in determining its visual quality, ensuring that the image does not become too dark or overexposed. A well-fused image should have a mean value that effectively balances the brightness while preserving important details from both input images.

5.2 ENTROPY (H)

Entropy is a measure of the randomness or information content in an image. It quantifies how much detail or uncertainty is present, with higher entropy indicating more complex and detailed textures, which is desirable in fused images. In image fusion, entropy helps assess whether the fused image retains essential information from the source images, ensuring no loss of critical details. A well-fused image should have higher entropy than individual source images, reflecting improved clarity and richness of information.

The Entropy is calculated using the formula:

$$H = -\sum_{i=0}^{L-1} p(i)\, log_2\, p(i) \qquad (5.2)$$

Where:

L = Total number of intensity levels in the image

p(i) = Probability of occurrence of intensity level i.

Entropy plays a crucial role in evaluating the effectiveness of fusion techniques, as a higher entropy value suggests that the fused image contains diverse and significant features from both input images.

5.3 STANDARD DEVIATION (σ)

Standard deviation measures the contrast and spread of intensity values in an image. It indicates how much pixel intensities deviate from the mean intensity, making it a crucial metric for assessing the sharpness and clarity of a fused image. A higher standard deviation signifies greater variation in intensity, which typically means better edge details and texture preservation. In image fusion, an optimal standard deviation ensures that the fused image retains significant structural information from both input images while enhancing visual quality. The Standard Deviation is calculated using the formula:

$$\sigma = \sqrt{\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (\mathrm{I}(\mathrm{i},\mathrm{j}) - \mu)^2} \quad \text{-----------------------------------} \quad (5.3)$$

Where:

M, N = Dimensions of the image (rows and columns).

I(i,j) = Intensity value at pixel (i, j).

μ = Mean intensity of the image.

A well-fused image should have a higher standard deviation compared to its source images, ensuring that important features such as edges, textures, and contrast are preserved, leading to better image quality for analysis and interpretation.

5.4 MUTUAL INFORMATION MI(1,2):

Mutual Information (MI) measures the amount of shared information between two images, indicating how much one image tells us about the other. In image fusion, mutual information is used to evaluate how well the fused image preserves information from the input images. A higher MI value suggests that the fused image retains more relevant details from both source images, making it more informative.

The Mutual Information (MI) is calculated using the formula:

$$MI(1,2) = \sum_i \sum_j p_{12}(i,j) log_2(\frac{p_{12}(i,j)}{p_1(i)p_2(j)}) \quad \text{---} (5.4)$$

Where:

P(12(i, j)) = Joint probability distribution of pixel intensities in images 1 and 2.

p1(i) = Probability distribution of pixel intensities in image 1.

p2(j) = Probability distribution of pixel intensities in image 2.

In fusion performance analysis, MI(A, F) and MI(B, F) are computed, where F is the fused image, to assess how much information from the original images is retained. A well-fused image should have high mutual information values with both input images, ensuring effective information preservation and fusion quality.

5.5 FUSION FACTOR (FF) :

Fusion Factor (FF) is a metric used to evaluate the effectiveness of an image fusion algorithm by measuring how well the fused image retains important information from the source images. It assesses the balance between the details preserved from both input images and their contribution to the final fused image. A higher fusion factor indicates that more relevant features have been successfully integrated, improving the overall quality of the fused image.

$$FF = \frac{MI(1,F)+MI(2,F)}{2} \quad \text{--(5.5)}$$

Where:

MI(1, F) = Mutual Information between Image 1 and the fused image F.

MI(2, F) = Mutual Information between Image 2 and the fused image F.

Fusion Factor provides a quantitative measure of fusion performance, ensuring that the fused image retains essential details from both input images while minimizing information loss. A well-fused image should have a high FF value, indicating an effective combination of features from both source images.

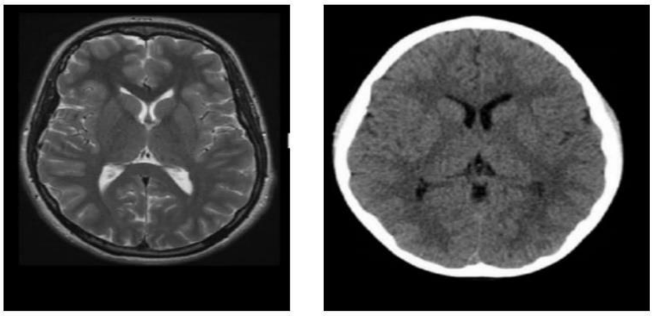
CHAPTER 6

RESULT AND DISCUSSION

The proposed work integrates various imaging modalities to enhance brain tumor detection and analysis. By utilizing multiple imaging techniques the aim is to provide a comprehensive understanding of the tumor's characteristics and progression. 50 images of Glioblastoma and 50 images of Meningioma were collected from the Online Repository, Brain Atlas, to ensure a reliable and extensive collection for analysis. The collected images were resized to 256×256 pixels for enhance resolution of images.

Compared CT and MRI images using Discrete Wavelet Transform (DWT) and Multi-resolution Singular Value Decomposition (MSVD) techniques. This analysis was crucial in highlighting the unique features and advantages of each modality. DWT decomposes the images into frequency components, providing detailed spatial and frequency information. MSVD captures and analyzes the multi-scale structure of the images, offering a more refined assessment of brain tumors. By integrating these advanced techniques, this project aims to enhance detection and analysis capabilities, leading to better diagnostic and treatment strategies for brain tumor patients.

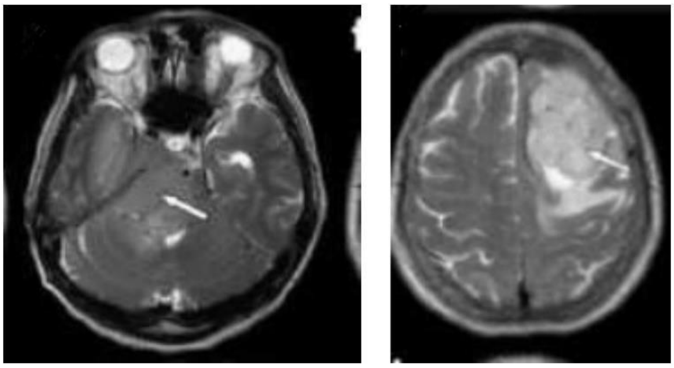
Figure 6.1 illustrates the input data set 1, showing an MRI scan and a CT scan of a Glioblastoma.



(a) b)

Figure 6.1 : Input data set 1: (a) MRI (b) CT of Glioblastoma.

Figure 6.2 illustrates the input data set 2, showing an MRI scan and a CT scan of a Meningioma.



(a) (b)

Figure 6.2 : Input data set 2: (a) MRI (b) CT of Meningioma.

The Figure 6.3 represents the fused image of Glioblastoma using DWT technique and Figure 6.4 represents the fused image of Glioblastoma using the MSVD technique.

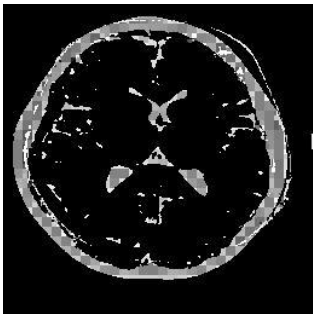


Figure 6.3 : DWT fused image of input data set 1

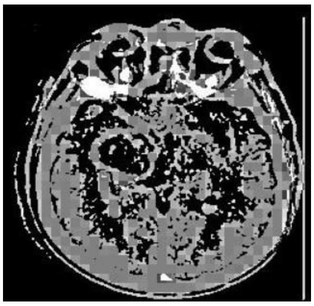


Figure 6.4 : MSVD fused image of input data set 1

The Figure 6.5 depicts the fused image of Meningioma using Discrete Wavelet Transform (DWT) technique and the Figure 6.6 depicts the fused images of Meningioma using Multi-resolution Singular Value Decomposition (MSVD) technique.

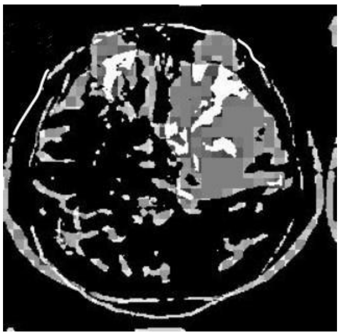


Figure 6.5 :DWT fused image of input data set 2

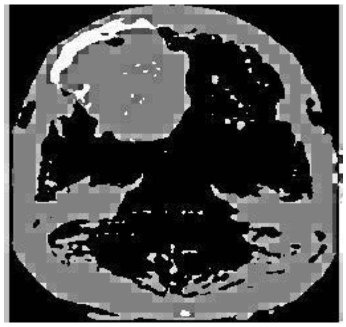


Figure 6.6 : MSVD fused image of input data set 2

STATISTICAL ANALYSIS

Quantitative analysis of performance metrics is represented in Table 6.1

Table 6.1 : Statistical Analysis of Performance Metrices

Data Set	**Metrices**	**DWT**	**MSVD**
Image Set 1 Glioblastoma	Mean	16.903	15.0901
	Entropy	5.5907	5.0000
	Standard Deviation	5.5907	8.5608
	Ma	0.4190	0.5680
	Mb	0.3647	0.175
	Fusion Factor	0.720	0.515
Image Set 2 Meningioma	Mean	14.6858	14.0001
	Entropy	6.0201	5.9980
	Standard Deviation	0.3637	0.612
	Ma	0.1626	0.590
	Mb	0.3544	0.178
	Fusion Factor	0.8170	0.510

Figure 6.7 represents the bar graph visualization of the mean values for Glioblastoma and Meningioma using DWT (red) and MSVD (blue) techniques. From the table, the mean for Glioblastoma is higher in DWT (16.9403) compared to MSVD (15.0901), which is reflected in the taller red bar. Similarly, for Meningioma, the DWT mean (14.6858) is slightly higher than MSVD (14.0001).

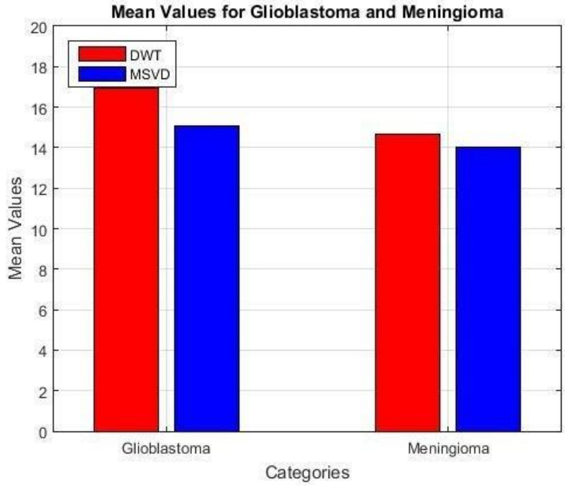


Figure 6.7: Graphical Representation of Performance Metric Mean

Figure 6.8 represents the bar graph visualization of the entropy values for Glioblastoma and Meningioma using DWT (red) and MSVD (blue) techniques. From the table, the entropy for Glioblastoma is higher in DWT (5.5907) compared to MSVD (5.0000), which is reflected in the taller red bar. Similarly, for Meningioma, the DWT mean (6.0201) is slightly higher than MSVD (5.9980).

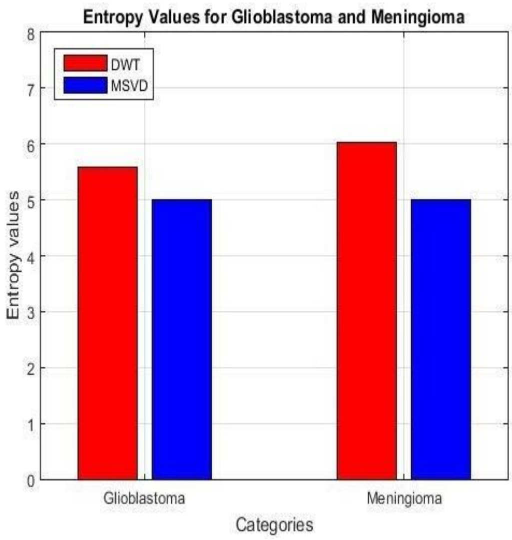


Figure 6.8: Graphical Representation of Performance Metric Entropy

Figure 6.9 represents the bar graph visualization of the standard deviation values for Glioblastoma and Meningioma using DWT (red) and MSVD (blue) techniques. From the table, the standard deviation for Glioblastoma is lower in DWT (5.5907) compared to MSVD (8.5608), which is reflected in the taller blue bar. Similarly, for Meningioma, the DWT mean (0.3637) is slightly lower than MSVD (0.612).

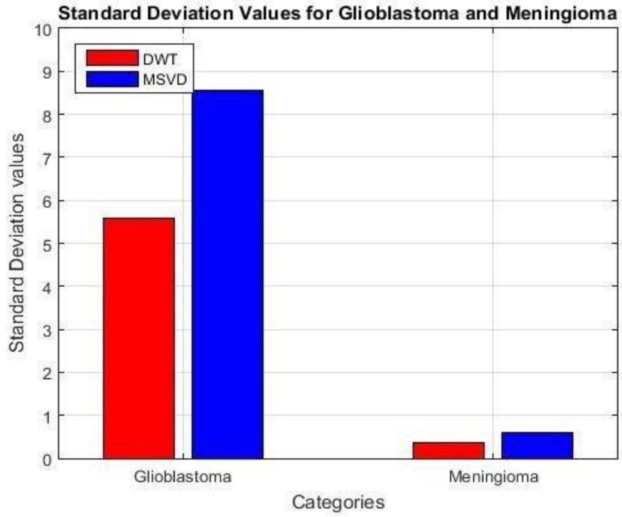


Figure 6.9: Graphical Representation of Performance Metric Standard Deviation

Figure 6.10 represents the bar graph visualization of the fused factor values for Glioblastoma and Meningioma using DWT (red) and MSVD (blue) techniques. From the table, the mean for Glioblastoma is higher in DWT (0.720) compared to MSVD (0.515), which is reflected in the taller red bar. Similarly, for Meningioma, the DWT mean (0.8170) is slightly higher than MSVD (0.510).

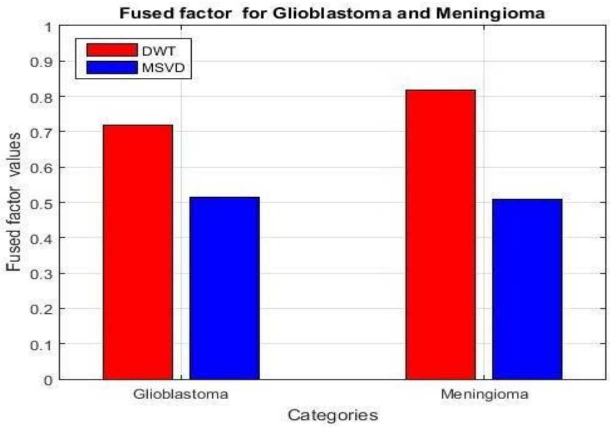


Figure 6.10: Graphical Representation of Performance Metric Fusion Factor

The data provided in the proposed project highlights several advantages of Discrete Wavelet Transform (DWT) over Multi-resolution Singular Value Decomposition (MSVD) in analysing mean, standard deviation, entropy, and fused factors for Glioblastoma and Meningioma.

DWT exhibits higher mean values for both Glioblastoma and Meningioma compared to MSVD, indicating better performance in capturing the overall intensity of the signals. For standard deviation, DWT consistently shows lower values than MSVD, reflecting less variability and more stability in the results.
In terms of entropy, DWT demonstrates higher values, suggesting that it can capture more complex and detailed information from the data, which is crucial for accurate medical diagnosis.

The fused factor values are also higher in DWT, indicating superior performance in combining information from different sources to produce a more comprehensive and accurate representation of the data.

These factors collectively demonstrate that DWT is more effective than MSVD for analysing and processing medical data related to Glioblastoma and Meningioma. The higher mean values, lower standard deviations, higher entropy, and better fusion capabilities make DWT a more reliable and robust technique for these applications.

CHAPTER 7

CONCLUSION

In this proposed work, we aim to integrate and fuse multi-modal medical imaging data to enhance the visualization and analysis of brain tumors. The proposed work compared the performance of Discrete Wavelet Transform (DWT) and Multi-resolution Singular Value Decomposition (MSVD) for the fusion of multimodal medical images in brain tumor detection and analysis. The results demonstrate that DWT outperforms MSVD in preserving vital diagnostic features such as tumor boundaries and metabolic activity. DWT's ability to effectively integrate structural and functional information from CT, MRI and PET images, while minimizing noise and artifacts, provides clear, more accurate representations for medical professionals, enhancing the diagnostic process and treatment planning.

The DWT-based fusion method offers superior computational efficiency, making it suitable for real-time clinical applications. The comparison highlights DWT’s robustness in retaining high-frequency details and ensuring a more stable and reliable image fusion, positioning it as a more effective tool than MSVD in medical imaging, particularly for brain tumor diagnosis. This study confirms that DWT is a promising technique for improving the quality of fused images and offers significant potential for application in oncology and other medical fields.

CHAPTER 8

APPLICATION AND FUTURE SCOPE

8.1 APPLICATION

Multimodal medical imaging is a powerful tool in the detection and analysis of brain tumors, leveraging the strengths of various imaging techniques such as MRI, CT, PET, and more. By combining these modalities, clinicians can obtain a comprehensive view of the brain's anatomy and tumor pathology, leading to more precise and personalized treatment plans. This approach is instrumental in diagnosing brain tumors at an early stage, planning surgeries with high precision, and monitoring the effectiveness of treatments.

MRI, for instance, provides detailed images of the brain's soft tissues, making it excellent for detecting tumors and assessing their growth. CT scans, on the other hand, offer rapid imaging and are particularly useful in emergency situations to quickly identify brain injuries. PET scans can be used to assess the metabolic activity of brain cells, helping to distinguish between malignant and benign tumors. By integrating these different imaging techniques, multimodal imaging provides a more accurate and complete picture of the brain, aiding in the accurate localization and characterization of brain tumors.

In addition to improving diagnostic accuracy, multimodal imaging is crucial for treatment planning. Surgeons can use the detailed images to plan precise surgical interventions, minimizing damage to healthy brain tissue. Oncologists can also use multimodal imaging to monitor the tumor's response to treatment, allowing for adjustments in therapy to achieve the best possible outcomes.

8.2 FUTURE SCOPE

The future scope includes the integration of real-time imaging by accessing live MRI scan data from neurologists and medical centers. This will enable seamless connectivity with hospital imaging equipment such as MRI and CT scanners, allowing instant processing and analysis for accurate tumor detection and classification.

Another important aspect of the future of multimodal medical imaging is the expansion of imaging modalities. By combining traditional techniques like MRI, CT scans, and PET scans with newer methods such as Ultrasound (US) and Optical Coherence Tomography (OCT) and advanced AI-based models, clinicians will be able to obtain a more comprehensive and detailed view of brain tumors. This holistic approach will improve diagnostic precision and enable more tailored treatment plans.

Furthermore, comparing advanced image analysis techniques such as Curvelet and Contourlet transforms will play a crucial role in optimizing imaging methodologies. Curvelet transforms are known for their ability to capture edges and smooth contours, while Contourlet transforms excel in representing directional features and textures. By evaluating these techniques, researchers can determine the most effective methods for specific imaging tasks, leading to better tumor detection and analysis.

Real-time imaging capabilities, expanded modalities, and the comparison of advanced techniques like Curvelet and Contourlet transforms will enhance diagnostic accuracy, treatment planning, and overall patient care. This integrated approach promises to revolutionize the field of neuro-oncology, offering more precise and personalized solutions for managing brain tumors.

REFERENCE

[1] Molham Moshantat, Saeid Karamzadeh , "CT and MRI Medical Image Fusion Using Discrete Wavelet Transform", Journal of Medical Imaging, Vol. 40-4 , pp. 939-945, 2019.

[2] M. Sajeer & Ashutosh Mishra . "A Robust and Secured Fusion-Based Hybrid Medical Image Watermarking Approach Using RDWT-DWT-MSVD with Hyperchaotic System Fibonacci Q Matrix Encryption", Multimedia Tools and Applications, Vol. 82, pp. 37479–37501, 2023.

[3] Jaskeerat Kaur, Sandhya, Priyanka Ganjoo, Musheer Vaqur, Kapil Joshi , "A Review: Image Fusion Using DCT and DWT", International Journal of Advanced Research in Computer Science and Software Engineering, Volume 10, Issue 2, ISSN 2229 5518, 2019.

[4] Gerald K. Ijemaru, Augustine O. Nwajana, Emmanuel U. Oleka, Richard I. Otuka, Isibor K. Ihianle, Solomon H. Ebenuwa, Emenike Raymond Obi, "Image Processing System Using MATLAB-Based Analytics", International Journal of Engineering and Technology, Vol. 10, No. 5, October 2021, pp. 2566-2577, 2021.

[5] Xin Jin , Qian Jiang , Xing Chu , Xun Lang , Shaowen Yao , Keqin Li and Wei Zhou, “Brain Medical Image Fusion Using L2-Norm-Based Features and Fuzzy-Weighted Measurements in 2-D Littlewood–Paley EWT Domain”, IEEE Transactions on Instrumentation and Measurement, Volume 69, Issue 8, in August 2020, on pages 5900-5913. The DOI for this publication is 10.1109/tim.2019.2962849. 2020.

[6] Kedar Nath Singh, Om Prakash Singh, Amit Kumar Singh, Amrit Kumar Agrawal, “WatMIF: Multimodal Medical Image Fusion-Based Watermarking for Telehealth Applications", Journal Cognitive Computation, Volume 16, in 2024, on pages 1947–1963. The DOI for this publication is 10.1007/s12559-022-10040-4. 16:1947–1963, 2020.

[7] M. D. Nandeesh, "Multimodal Image Fusion using Hybrid Algorithms for Brain Tumor Detection", IEEE Mysore Sub Section International Conference (MysuruCon), Hassan,

India, pp. 566-571, doi: 10.1109/MysuruCon52639.2021.9641592, 2021.

[8] M. Poshitha, K. Ramaraj, S. Dilipkumar, R. Durga Meena, B. Ambika and M. Thilagaraj, "Weighted Fuzzy C Means: A Novel Tumor Segmentation Approach in MR Brain Images", 2023 2nd International Conference on Automation, Computing and Renewable Systems (ICACRS), Pudukkottai, India,pp. 574-581, doi: 10.1109/ ICACRS58579. 2023. 10404219, 2023.

[9] C. M. B. M J, E. Kannan, A. D. S, G. Thangarasu and A. Begum, "Enhanced Brain Tumor Diagnosis through Multimodal Fusion and 3D Convolutional Neural Networks", 2023 Second International Conference On Smart Technologies For Smart Nation (SmartTechCon), Singapore, Singapore, pp. 1371-1375, doi: 10.1109/ SmartTechCon57526.2023. 10391443, 2023.

[10] Ankur, M. Gupta, R. Kumar and P. Zanke, "A comprehensive Analysis on ResNet-Based Techniques for Brain Tumor Detection", 2024 First International Conference on Technological Innovations and Advance Computing (TIACOMP), Bali, Indonesia, pp. 455-461, doi: 10.1109/TIACOMP64125.2024.00082, 2024.

[11] M. Fan, "Research on Feature Detection Based on Convolutional Network with Deep Instance Segmentation", 2021 IEEE International Conference on Data Science and Computer Application (ICDSCA), Dalian, China, pp. 538-543, doi: 10.1109/ICDSCA53499.2021.9650185, 2021.

[12] M. D. Meenakshi and M. D Nandeesh, "Tumor Detection Using Enhanced FCM for Multimodal Brain Images", 2019 2nd International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT), Kannur, India, pp. 1419-1422, doi: 10.1109/ICICICT46008.2019.8993400, 2019.

[13] Rui Zhu, Xiongfei Li, Xiaoli Zhang, Mingrui Ma . "MRI and CT Medical Image Fusion Based on Synchronized-Anisotropic Diffusion Model", published in IEEE Access, Vol. 8, Article 2993493, doi: 10.1109/ACCESS. 2020.2993493, 2020.

[14] https://doi.org/10.1016/j.jare.2014.01.005