Combinatorial Multimodal Fusion to Enhance Brain Tumor Image Using Discrete Wavelet Transform.

Samuel Iorhemen AYUA[1*], E. J. Garba[2], Y. M. Malgwi[3]

[1]Computer Science, Taraba State University Jalingo, Nigeria

[2,3]Computer science, Modibbo Adama University Yola, Nigeria

ABSTRACT

Multimodal brain imaging combines structural and functional medical images to improve diagnostic accuracy in neurological analysis. However, the fusion of heterogeneous modalities such as MRI, CT, and PET remains challenging due to variations in contrast, spatial resolution, and noise. This paper proposes a novel combinatorial multimodal fusion framework based on the Discrete Wavelet Transform (DWT) that integrates complementary information from the combination of multiple brain imaging modalities. The method employs combinatorial analysis of modalities in different ways, multi-resolution wavelet decomposition, and adaptive fusion rules to maximize structural preservation and functional enhancement. The wavelet decomposition of the dataset has been done at four levels with low and high activity regions.

Quantitative evaluation using Entropy (EN), Mutual Information (MI), Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), Fusion Factor (FF), and Edge Preservation Index (EPI) demonstrates that the proposed approach outperforms conventional PCA, Laplacian pyramid, Discrete Cosine Transform (DCT), and basic DWT methods. The resulting fused images exhibit superior clarity, contrast, and diagnostic utility. This proposed method gives 98.34% accuracy for the fusion using PSNR. The experiment is tested over the Daubechies (db4) wavelet approach. The quantitative and graphical analysis indicates that the Discrete Wavelet Transform (DWT) significantly improves the quality of fused images among other fusion methods.

Keywords: Combinatorial, Multimodal, Brain, Dataset, Discrete, Wavelet, Transformation.

INTRODUCTION

In the medical science, the image processing techniques plays a significant function. Computational automation of the treatment is a most authentic and prominent method. Medical diagnosis relies heavily on the accurate detection and localization of abnormalities in medical images. A misdiagnosed brain tumor results in ineffective medical treatment, which lowers the chances of survival for the patient (Rathod and Khan, 2021; Senan *et al*., 2022).

Different types of medical imaging and diagnostic techniques are used to obtain information related to tumors. Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) are methods for identifying normal and abnormal growing cells in the brain (Huang *et al*., 2021; Huang *et al*., 2022). The CT scan is used to diagnose patient using an X-ray and the computer to create the brain images in the axial fragments (Bekhet *et al*., 2020; Fahmi *et al*., 2020; Mubashar *et al*., 2022); while MRI creates 2D and 3D images of the body's internal organs without pain or needing surgery (Alanazi *et al*., 2022).

According to Azam *et al.,* (2022); in image processing, the image fusion is a method of merging two or more images into a single picture. The obtained single fused image using various multimodality medical images enhanced anatomical, highly desirable spectral information compared to the raw single scanned image. This multimodal fused image is useful for expert clinical diagnosis.

According to kaur *et al.,* (2021), the goal of Image Fusion (IF) is to produce a merged image with the integration of Information from more than one imaging modalities. **Figure 1** demonstrates the major steps

involved in IF process. In wide-ranging, the registration is measured as an optimization issue which is used to exploit the similarity as well as to reduce the cost. The Image registration procedure is used to align the subsequent features of various images with respect to a reference image (Wang *et al.,* 2021). In this procedure, multiple source images are used for registration in which the original image is recognized as a reference image and the original images are aligned through reference image.

In feature extraction, the significant features of registered images are extracted to produce several feature maps (Li *et al.,* 2024). By employing a decision operator whose main objective is to label the registered images with respect to pixel or feature maps, a set of decision maps are produced. Semantic equivalence obtained the decision or feature maps that might not pass on to a similar object and is employed to connect these maps to a common object to perform fusion (Weng *et al.,* 2024).

kaur *et al.,* (2021) stated that multimodal medical imaging process is redundant for the source obtained from a similar kind of sensors. Then, radiometric calibration is employed on spatially aligned images. Afterward, the transformation of feature maps is performed on an ordinary scale to get end result in a similar representation format. Finally, IF merge the consequential images into a one resultant image containing an enhanced explanation of the image. The main goal of fusion is getting more Informative fused image (kaur *et al.,* 2021).
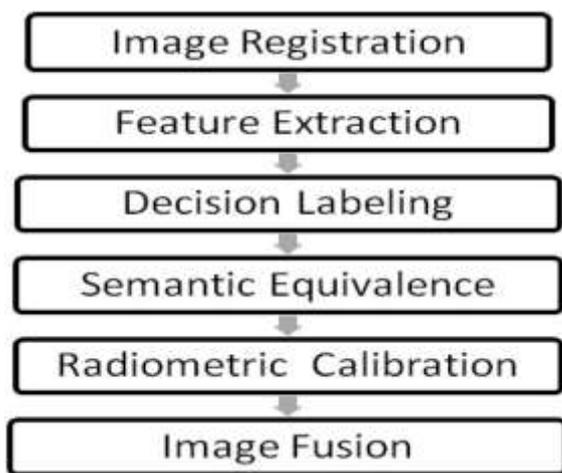
Figure 1: Steps in IF Process. Source: (Kaur *et al.,* 2021)

Neuroimaging modalities provide critical and complementary insights into brain structure and function as shown below:

i.   **MRI** offers high-resolution soft-tissue contrast.

ii. **CT** highlights bone structures and calcifications.

iii. **PET/SPECT** visualize metabolic and perfusion activity.

No single modality alone provides a complete characterization of brain abnormalities. Multimodal fusion addresses this limitation by combining high-structural and high-functional information into a single, unified image (Huang *et al,* 2020).

In many healthcare settings, the scarcity of experienced radiologists, combined with limited access to high quality imaging equipment or the use of only a single imaging modality to obtained image, impedes reliable diagnosis. Furthermore, selecting the most suitable image from imaging modalities for a given diagnostic task often relies on manual judgment, which can be prone to error.

Research conducted by Ramaraj *et al.* (2024), Srikanth *et al.* (2024) and Usha *et al.* (2024) reviews that most of researchers used two imaging modalities. This restricts the exploration of other imaging modalities, and their potential contribution to improving diagnosis when they are combined in various ways. Supporting the above, Azeez and Abdulazeez (2025) suggested the integration of multimodal imaging data by combining MRI, CT, and PET to improve diagnostic outcomes.

Wavelet-based fusion has gained traction due to its ability to encode images into multi-scale frequency bands while preserving spatial details. However, existing DWT-based fusion frameworks typically combine only two modalities without consideration on various ways of combination, which may lack adaptive feature selection.

To address these limitations, the current research proposes a novel approach that automatically combines three imaging modalities (MRI, CT, and PET) to obtain seven combinations. This different combination of images in different ways is expected to provide a richer and more informative representation of tumor characteristics, thereby enhancing the fused images. Finally Discrete Wavelet Transform (DWT) was employed to perform image fusion across images in different modality combinations and Peak Signal-to-Noise Ratio (PSNR) was used as an evaluation metric to identify the most effective fused images.

Table 1 summary and comparison of the related works using traditional machine learning and deep learning models

Authors/ and Year	Research Title	Method/s used	Dataset used	Problem addressed
Ramaraj *et al.* (2024)	Medical Image Fusion for Brain Tumor Diagnosis Using Effective Discrete Wavelet Transform Methods	Discrete Wavelet Transform (DWT) and Inverse Discrete Wavelet Transform (IDWT)	MRI and CT dataset	The researcher worked on preserving the colour of the source image in the fused image after performing image fusion to maintain the image fidelity and spectral integrity to aid decision making.
Srikanth *et al.* (2024)	Brain Tumor Detection through Image Fusion Using Cross Guided Filter and Convolutional Neural Network	Cross Guided Filter and Convolutional Neural Network	MRI and CT dataset	The researcher worked on preserving and improving the quality of the fused iamge.
Usha *et al.* (2024)	Multimodal Brain Tumor Classification Using Convolutional Tumnet Architecture	Convolutional Tumnet Architecture	MedHarvard database (MRI and CT dataset)	Problem of accurate classification and decision support for oncologists.
Vankdothu *et al.* (2022)	Brain tumor MRI images identification and classification based on the recurrent convolutional neural network	Recurrent Convolutional Neural Networks (RCNN).	MRI dataset	Improving the accuracy of brain tumor detection and classification.
Alemu *et al.* (2023)	Magnetic resonance imaging-based brain tumor image classification performance enhancement	Support Vector Machine (SVM), and compared with deep learning techniques.	MRI dataset	Brain tumor classification method based on Support Vector Machine (SVM) using MRI images

Authors/ and Year	Research Title	Method/s used	Dataset used	Problem addressed

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Jiang & Kumar, (2023)	Magnetic resonance imaging (mri) brain tumor image classification based on five machine learning algorithms	k-Nearest Neighbors, decision tree, Support Vector Machine, logistic regression, and Stochastic Gradient Descent	MRI dataset	Utilizing machine learning models to classify MRI brain tumor images, and comparing the performance of five different models.
Alzahrani (2023)	Brain tumor detection and type classification using convolutional mixer with external and self-attention mechanisms	ConvAttenMixer	MRI dataset	multimodal medical image fusion model utilizing Modified DWT with an Arithmetic Optimization Algorithm for brain tumor detection and classification
Raghuram *et al.* (2023)	Brain tumor image identification and classification on the internet of medical things using deep learning	K-Means Clustering and a Support value based deep neural network (SDNN)	MRI dataset	Enhancing brain tumor detection in MRI images through segmentation and classification techniques
Huang *et al.* (2020)	A review of multimodal medical image fusion techniques	Conducted a review on image fusion methods on medical image fusion research.	NAP	Different image fusion methods on medical image fusion, advantages of different methods and fusion effect
Noor *et al.* (2020)	Hybrid image fusion method based on discrete wavelet transform (DWT), principal component analysis (PCA) and guided filter	hybrid approach using Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA) and Guided filter.	MRI and CT Brain dataset from Atlas Harvard Medical School	Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA) and Guided filter for brain tumor classification.
Zhou *et al.* (2024)	Multimodal medical image fusion network based on target information enhancement	target information enhanced image fusion network (TIEF)	ANNLIB (SPECTMRI and CT-MRI) dataset	Enhancing brain tumor detection using Multi-modal MRI image fusion method, and necrotic tumor core in different modalities to generate a fusion image with rich texture information and clear structure
Kaur *et al.* (2021)	Image fusion techniques: a survey	a survey on various image fusion techniques	NAP	Survey on various image fusion techniques with their pros and cons, different methods with state-of-art.

Authors/ and Year	Research Title	Method/s used	Dataset used	Problem addressed
Sun *et al.* (2024)	Multi-modal Medical Image Fusion Approach Utilizing Gradient Domain Guided Image Filtering	multi-channel fusion algorithm based on gradient domain guided image Filtering	Public and non-public dataset	Enhancing the color preservation of source images in multimodal medical image fusion algorithms
Moghtaderi *et al.* (2024)	Advancing multimodal medical image fusion: an adaptive image decomposition approach based on multilevel Guided filtering	multilevel Guided edge-preserving filtering (MLGEPF)	MRI, SPECT, PET dataset	Preserving information from diverse sensors using various models to generate a single informative image; that will be fast and reliable for MLGEPF decomposition rule.
Sridevi (2021)	Image Fusion Algorithm for Medical images using DWT and SR	DWT and sparse representation (SR)	MRI, CT, PET dataset	Combining multimodal images of MRI/CT/PET using DWT and sparse representation (SR) for diagnosis of ailments and treatment at early stages
Alzahrani (2024)	Enhanced multimodal medical image fusion via modified DWT with arithmetic optimization algorithm	Modified DWT with an Arithmetic Optimization Algorithm (MMIFMDWTAOA), bilateral filtering (BF)	Medicinal image database dataset	Create a combined image that holds the essential details and factors from each modality, leading to a detailed depiction for accurate interpretation by medical professionals
Mahdi *et al.* (2024)	Weighted Fusion Transformer for Dual PET/CT Head and Neck Tumor Segmentation	Weighted Fusion Transformer Network, Fusion FormerU-Net architecture.	Multiinstitutional PET/ CT image dataset	Accurate tumor segmentation in PET/CT imaging for the diagnosis and treatment of cancer, impacting therapeutic outcomes and patient management.
Abdulkareem (2018)	Design and development of multimodal medical image fusion using discrete wavelet transform	Discrete Wavelet Transform (DWT)	PET and MRI dataset	Medical expert needs a solid strain of the computational scan and it's related for diagnosis. The diagnosis and treatment of disorders requires precise information that is attained through various modalities of medical images, wavelet based fusion approach for the PET and MRI image was considered.

Authors/ and Year	Research Title	Method/s used	Dataset used	Problem addressed
Zebari *et al.* (2024)	A deep learning fusion model for accurate classification of brain tumours in Magnetic Resonance images	VGG16, ResNet50, and convolutional deep belief networks networks (CDBN)	MRI dataset from kaggle dataset	To extract deep features from MRI images and perform classification of brain tumor into four categories.
Wu *et al.*	DCFNet: Infrared and	discrete wavelet	TNO, NIR,	The research addresses the
(2024)	Visible Image Fusion Network Based on DiscreteWavelet Transform and Convolutional Neural Network.	transform and convolutional neural networks	and RoadScene datasets	issues of missing detailed information, the blurring of significant target information, and poor visual effects in current image fusion algorithms.

METHODOLOGY

This section discussed the methodology employed to achieve the aim and objectives of the study; it helps to plan, organize, and implement image fusion research from one step to another; The Python programming language, image quality evaluation, and other libraries specifically for image fusion research were also discussed.

Dataset population and description

The dataset was collected from Kaggle website and other related medical imaging data sources, which are the publically available database and other consultation from specialist hospital Jalingo Taraba state giving a total of 1500 images, each class having 500 images. This dataset include both healthy brains and brains with tumors, considering different types of brain tumors classes (e.g., glioma, meningioma, pituitary tumor etc.).

The collected image dataset from the three imaging modalities were cleaned and preprocess (e.g., image registration, resizing, noise reduction, contrast enhancement); normalize and standardize the images. This dataset was converted into the proper format (JPG) with accurate annotations and made ready for image fusion.

Method and development tools

This research utilized wavelet as a method for image fusion, discrete wavelet transformation as technique/model, Jupyter Notebook within the Anaconda Navigator cross platforms for model building, alongside Python libraries and modules/libraries such as scikit-learn, NumPy, Pandas, and Matplotlib for implementation and analysis.

The proposed fusion model architecture

As shown in **Figure 2,** this study firstly, combine three medical imaging modalities (MRI, CT, and PET), where seven combination: MRI, CT, PET, [MRI, PET], [PET, CT], [MRI, CT], [MRI, CT, PET] were generated. To evaluate the fusion performance, standard image fusion metrics were computed and examined, including Entropy (EN), Mutual Information (MI), Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), Fusion Factor (FF), and Edge Preservation Index (EPI); and the best fused images were selected using PSNR due to its high level of its effectiveness for retaining the quality of the fused images.
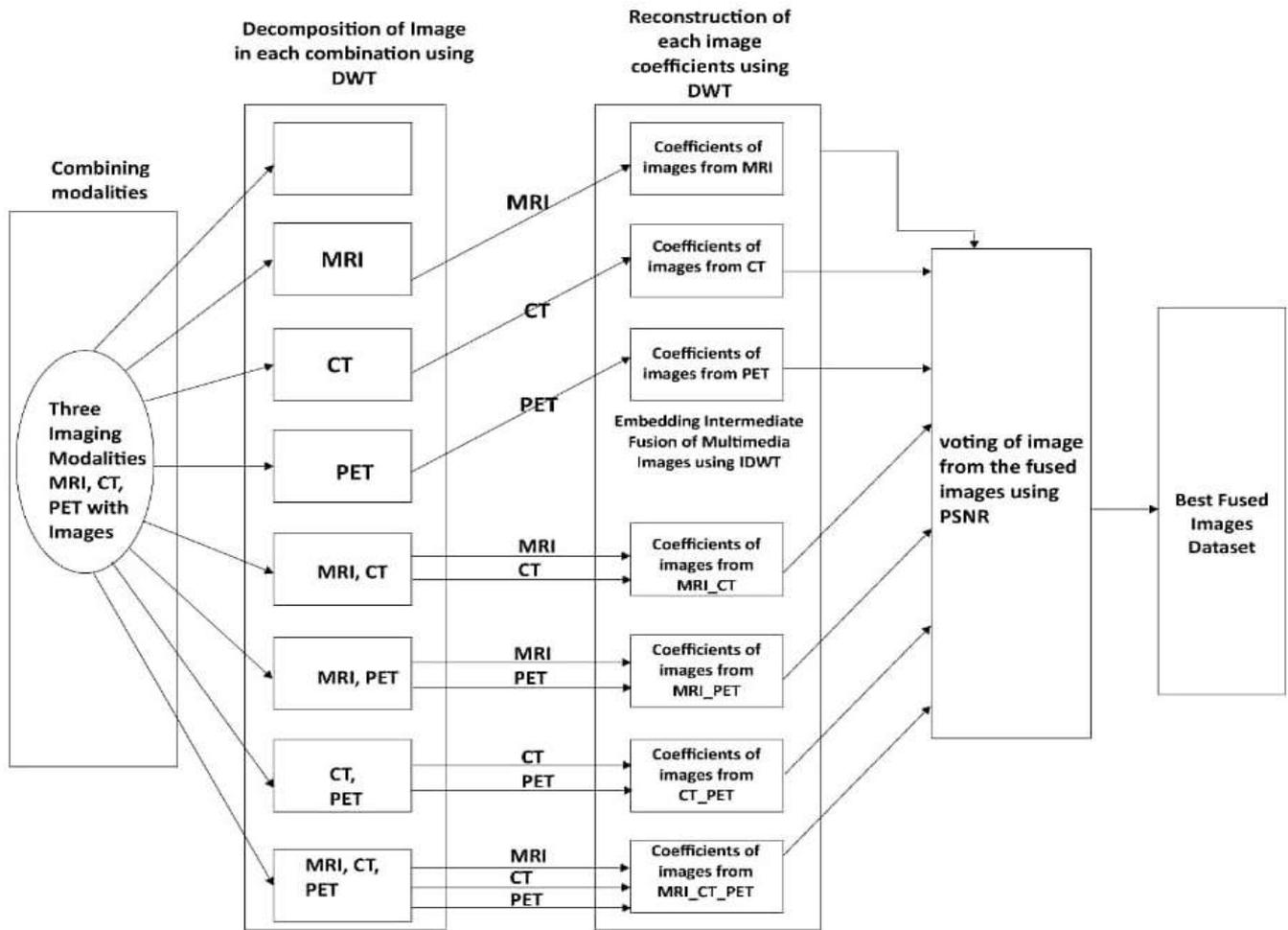
Figure 2: Block diagram combining three medical imaging modalities (MRI, CT, and PET) and performing both DWT and IDWT on each of the image in the combinations.

Performing combination on three imaging modalities and image fusion.

Step 1: Three medical imaging modalities (MRI, CT and PET) were used to collect brain images.

Step 2: Three medical imaging modalities (MRI, CT and PET) were combined, to obtain seven combinations: MRI, CT, PET, [MRI, PET], [PET, CT], [MRI, CT], [MRI, CT, PET].

Step 3: Transformation technique (DWT) was applied on every image within each medical imaging modality combinations to obtain the wavelet coefficient for each images.

i. Considering a single medical imaging modality the Discrete Wavelet Transform (DWT) decomposes the image into low and high-frequency components. A fusion rule is then applied, followed by the Inverse Discrete Wavelet Transform (IDWT) for reconstructing the features of the fused frequencies. This process results in a fused image representative of any of the four tumor classifications being considered.

ii. In two medical imaging modalities are examined. The Discrete Wavelet Transform (DWT) breaks down the images into low and high frequency components for each modality. Specifically, the low frequency component from modality 1 is combined with the high frequency component from modality 2, and vice versa. A fusion rule is then applied, and the Inverse Discrete Wavelet Transform (IDWT) is used to reconstruct the features from the fused frequencies. This process

results in a fused image tailored to effectively represent any of the four types of tumors under study.

iii.   In considering three medical imaging modalities, the Discrete Wavelet Transform (DWT) will decompose each image into low and high-frequency components. The low-frequency component from modality 1 will be combined with the high-frequency component from modality 2, and vice versa. A fusion rule will be applied, followed by an Inverse Discrete Wavelet Transform (IDWT) to reconstruct the features of the fused frequencies, resulting in a fused image. This fused image will then be decomposed again using DWT into its low and high-frequency components. The lowfrequency component of the fused image will be combined with the high-frequency component from modality 3, and vice versa. Finally, another fusion rule will be applied, and IDWT will be used to reconstruct the features of the new fused frequencies, leading to the final fused image tailored to represent any of the four types of tumors under study.

iv.   Repeat **Step 3** for all images in each medical imaging modality within every combination to obtain the augmented fused images classified according to the four tumor types.

Step 4: PSNR was used for each combination of medical imaging modalities image to evaluate and obtained highest quality fused images, which correspond to any of the four tumor classes; and were used to create a new brain tumor dataset.

As shown in the **Figure 2** above; in every combination, transformation technique (DWT) as shown in **Equation 1**, was applied on every image to four-level decomposition and obtained the wavelet coefficients. After decomposition, corresponding sub-bands of the images are fused using a fusion rule as shown in **Equation 2** and finally, IDWT as shown in **Equation 3** was used for the feature reconstruction of the fused frequencies to obtain the final fused image. The fused image F(x,y) is obtained by applying a four-level inverse discrete wavelet transform (IDWT) to the fused approximation coefficients FLL_J and the fused detail coefficients.

$$DWT_J\{I_k\,(x,\ y)\} = \left\{LL_J^{(k)}, \left\{LH_j^{(k)},\ HL_j^{(k)}, HH_j^{(k)}\right\}_{j=1}^{J}\right\} \qquad\qquad \textbf{Equation (1)}$$

Where:

$I_k\,(x,\ y)$: k-th source image $(k = 1, 2)$

(x, y) is Spatial coordinates (pixel indices)

$LL_0^{(k)}$: Initial approximation sub-band

$LL_J^{(k)}$: Approximation sub-band at level j

$LH_j^{(k)}$: Horizontal sub-band

$HL_j^{(k)}$: Vertical sub-band

$HH_j^{(k)}$: Diagonal sub-band

j: Decomposition level index $(1 \leq j \leq J)$

$DWT_j\{.\}$: Discrete wavelet transform at level j

$$F_S(j, x, y) = \begin{cases} S_j^{(1)}(x, y), & \left|S_j^{(1)}(x, y)\right| \geq \left|S_j^{(2)}(x, y)\right| \\ S_j^{(2)}(x, y), & otherwise \end{cases} \quad S \in \{LH, HL, HH\} \qquad \text{Equation (2)}$$

Where:

$F_S(j, x, y)$: Maximum selection fusion rule result

S: Sub-band identifier where: $S \in \{LH, HL, HH\}$

LL, LH, HL, HH: Approximation and sub-bands

J: Decomposition level, j = 1… J

(x, y): Spatial coordinates (pixel indices)

$S_j^{(1)}(x, y)$: Sub-band coefficient of the first source image at level j

$S_j^{(2)}(x, y)$: Sub-band coefficient of the second source image at level j

$|.|$: Absolute value operator

Finally, the fused image is reconstructed by the inverse DWT (IDWT):

$$F(x, y) = IDWT_J \left\{FLL_J, \{FLH_j, \ FHL_j, FHH_j\}_{j=1}^J\right\} \qquad \text{Equation (3)}$$

Where:

$F(x, y)$: Final Fused image

(x, y): Spatial coordinates (pixel indices)

J: Decomposition level, j = 1… J

$IDWT_J$: J-level inverse discrete wavelet transform

FLL_J: Fused approximation coefficients at highest level

$FLH_j, \ FHL_j, FHH_j$: fused detail coefficients

Image Fusion Model Evaluation

To assess fusion performance, standard image fusion metrics were computed, including EN, MI, SSIM, PSNR, FF, and EPI on individual, combined and the selected combined modalities images.

RESULTS AND DISCUSSION

The experimental dataset of brain images were acquired from three different imaging modalities: Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Positron Emission Tomography (PET). Each modality provides unique diagnostic information: MRI highlights soft tissues and brain structures, CT provides bone and density contrast, and PET visualizes metabolic activity. The processed dataset contains 1500 brain images with 500 from each modality, as shown in **Table 2**, and a total of four classes are considered (glioma, meningioma, pituitary tumor, and healthy brain), as shown in **Table 3**, aligned to the objectives of the research.

Table 2: Imaging Modality considered with total images.

Imaging Modality	Images in each Modality
MRI	500
CT	500
PET	500
Total	**1500**

Table 3: Classes of the Brain tumor considered.

Class of Brain tumor	Images in each brain tumor class
Glioma	125
Meningioma	125
Pituitary	125
Healthy Brain	125
Total	**500**

The Images dataset were resized to a uniform dimension of 256×256 pixels and converted to grayscale intensity images for compatibility with the DWT fusion process. The labelled brain image were read into jupyter notebook as shown in **Figure 3**
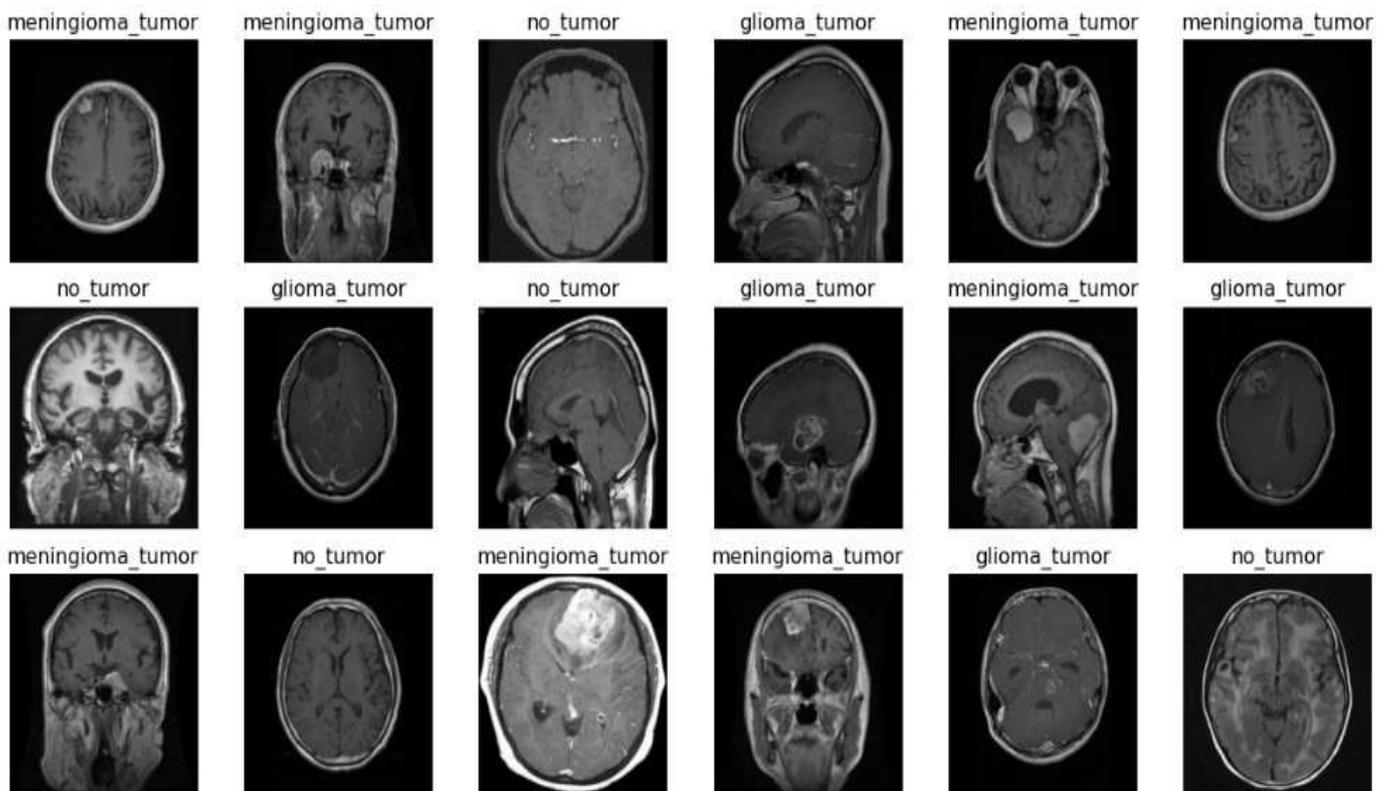
**Figure 3: Brain Image resizing to uniform dimension (256 x 256)**

As shown in **Table 4**, seven combinations were generated from the available imaging modalities to create dataset of brain images across these three imaging modalities, to assess the effect of different fusion performance.

Table 4: Modality Combinations Generated

S/No	Modalities considered			Modality Combination
	MRI	**CT**	**PET**	
1	-	-	PET	PET
2	-	CT	-	CT
3	MRI	-	-	MRI
4	MRI	CT	-	MRI + CT
5	-	CT	PET	CT + PET
6	MRI	-	PET	MRI + PET
7	MRI	CT	PET	MRI + CT + PET

The DWT was employed for fusing the multimodal images. Each image was decomposed into approximation (low-frequency) and detail (high-frequency) coefficients using a two-level db4 wavelet. The approximation coefficients were combined using a weighted averaging rule, while the detail coefficients were fused using a maximum selection rule to retain edge and boundary information.

The Inverse DWT (IDWT) reconstructed the fused images, which demonstrate visual results for selected combinations. The fused images from [MRI + PET], [MRI + CT], [PET + CT], and [MRI + CT + PET] combinations shown in **Figure 4** improved contrast, clearer structural outlines, and enhanced visibility of potential tumor regions compared to individual modality images.
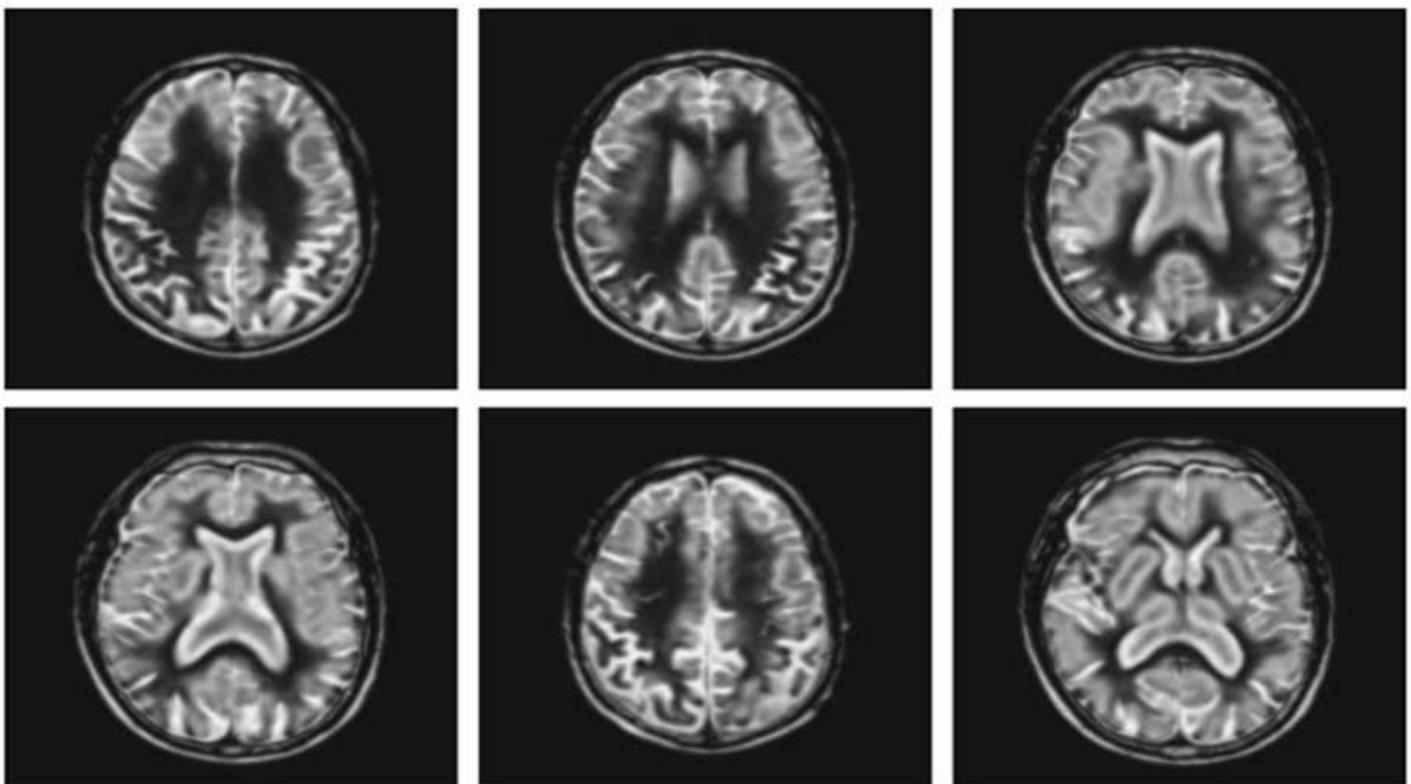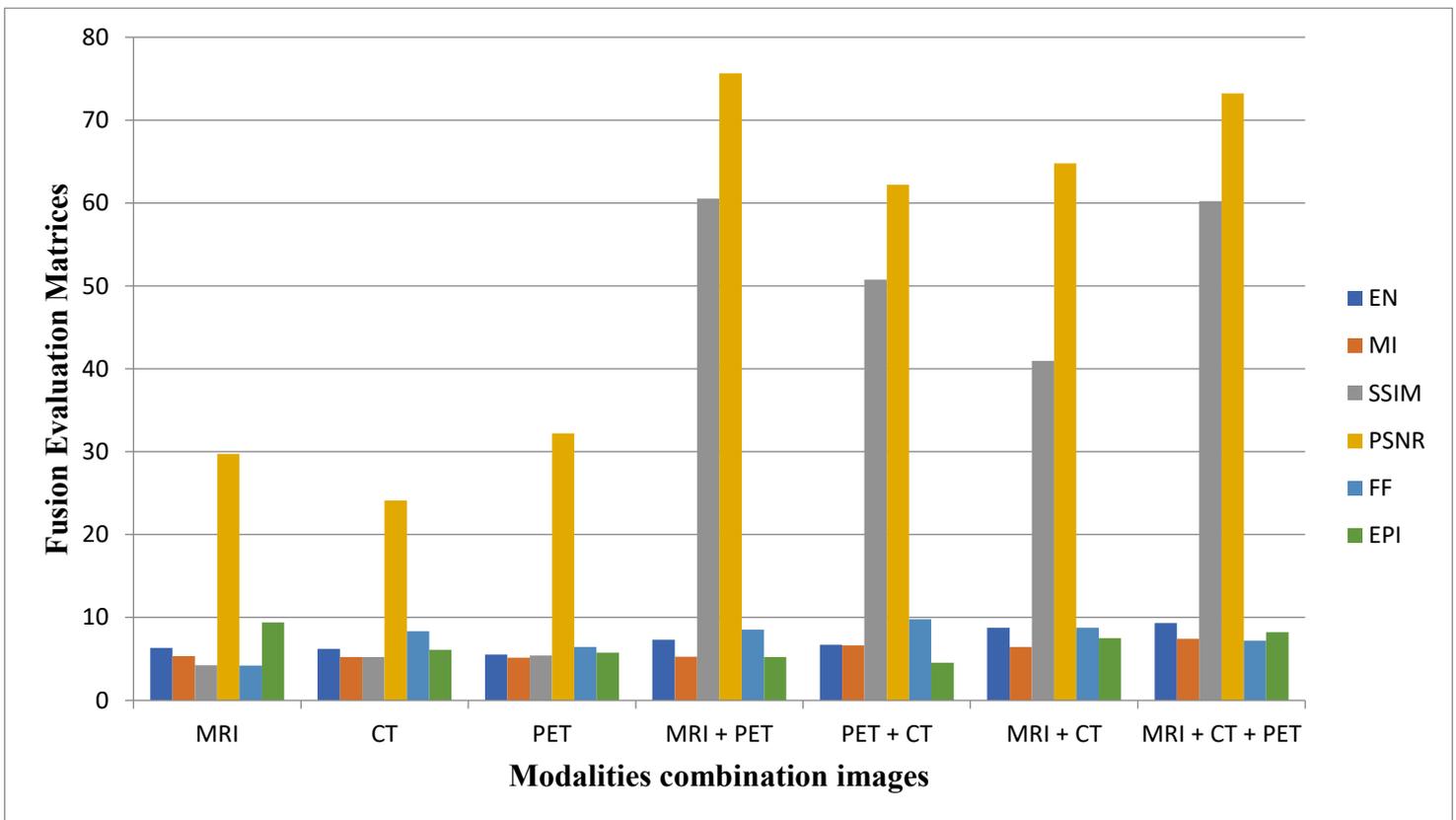

 Figure 4: Fused images based on modality combinations

Standard image fusion metrics such as Entropy (EN), Mutual Information (MI), Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), Fusion Factor (FF), and Edge Preservation Index (EPI) were

used to evaluate fusion performance on the imaging modality combination considered. **Tables 5** to **8** and **Figures 5** to **8** summarized the findings based on images from Modality Combination, Evaluation Metrics, and the fusion techniques applied.

Table 5: Evaluation based on images in Modality Combination and Evaluation Metrics using PCA Fusion

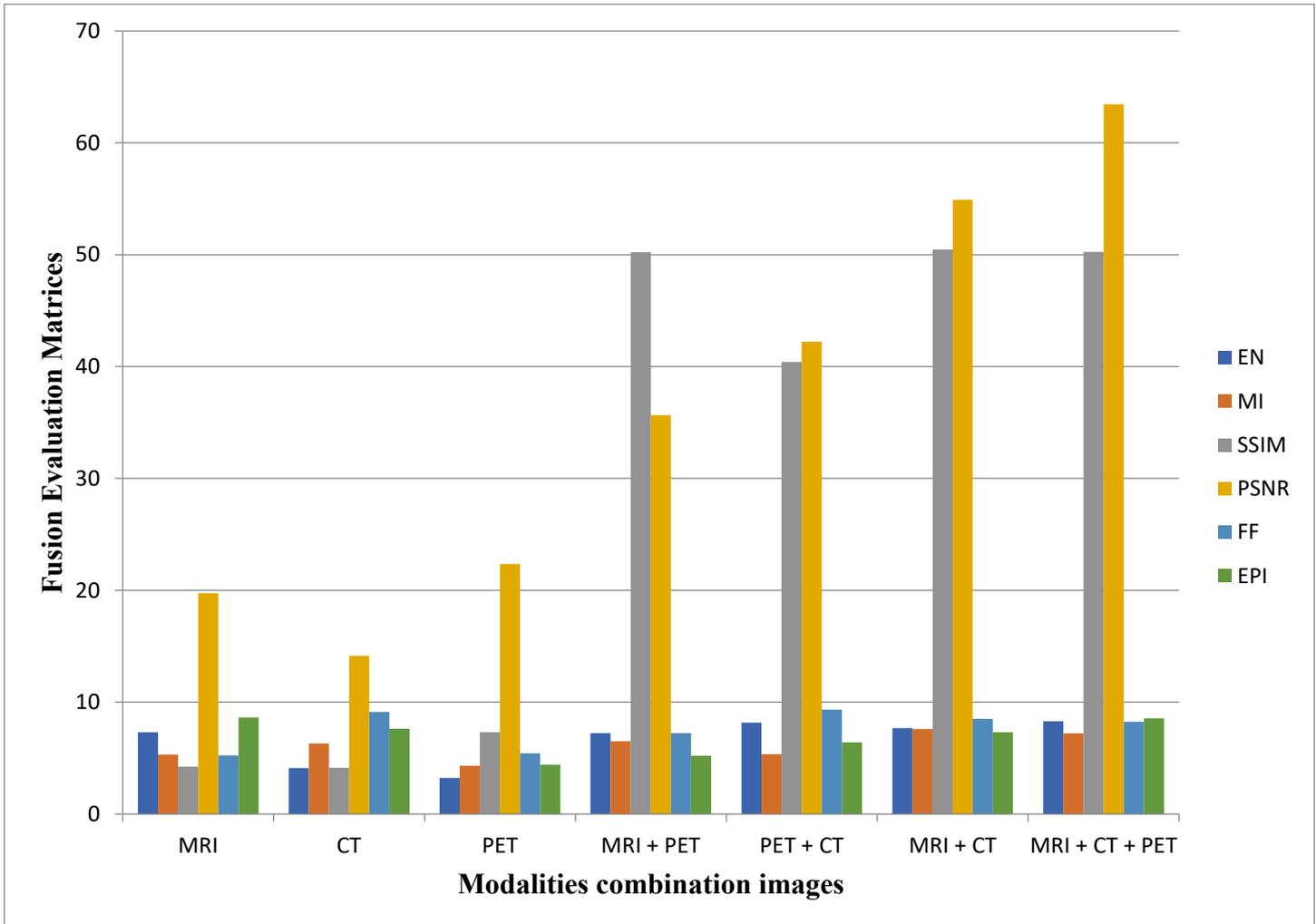| Modality Combination	EN	MI	SSIM	PSNR	FF	EPI
MRI	6.33	5.33	4.24	29.73	4.21	9.42
CT	6.21	5.23	5.22	24.11	8.33	6.11
PET	5.52	5.14	5.43	32.22	6.44	5.77
MRI + PET	7.32	5.25	60.52	75.67	8.55	5.24
PET + CT	6.71	6.63	50.74	62.21	9.77	4.54
MRI + CT	8.76	6.46	40.96	64.77	8.78	7.51
MRI + CT + PET	9.33	7.44	60.24	73.21	7.21	8.24

Figure 5: Modality image Combination Evaluation using PCA Fusion

Table 6: Evaluation based on images in Modality Combination and Evaluation Metrics for LP Fusion

Modality Combination	EN	MI	SSIM	PSNR	FF	EPI
MRI	7.33	5.33	4.24	19.73	5.24	8.64
CT	4.12	6.32	4.13	14.15	9.12	7.62
PET	3.24	4.31	7.33	22.34	5.43	4.43

MRI + PET	7.24	6.52	50.22	35.65	7.25	5.22
PET + CT	8.17	5.35	40.41	42.24	9.33	6.41
MRI + CT	7.67	7.61	50.45	54.92	8.51	7.32
MRI + CT + PET	8.31	7.22	50.24	63.44	8.25	8.55

Figure 6: Modality image Combination Evaluation using LP Fusion

Table 7: Evaluation based on images in Modality Combination and Evaluation Metrics for DCT Fusion

Modality Combination	EN	MI	SSIM	PSNR	FF	EPI
MRI	5.21	5.34	5.21	35.87	5.29	5.23
CT	4.23	5.23	4.28	34.23	4.23	4.22
PET	5.54	5.14	5.54	35.44	5.54	5.54
MRI + PET	6.26	5.27	46.29	58.56	6.27	6.21
PET + CT	6.79	6.63	36.77	58.43	6.74	6.78
MRI + CT	5.96	6.46	45.96	56.12	5.96	5.96
MRI + CT + PET	7.24	7.44	47.24	58.27	7.24	7.24
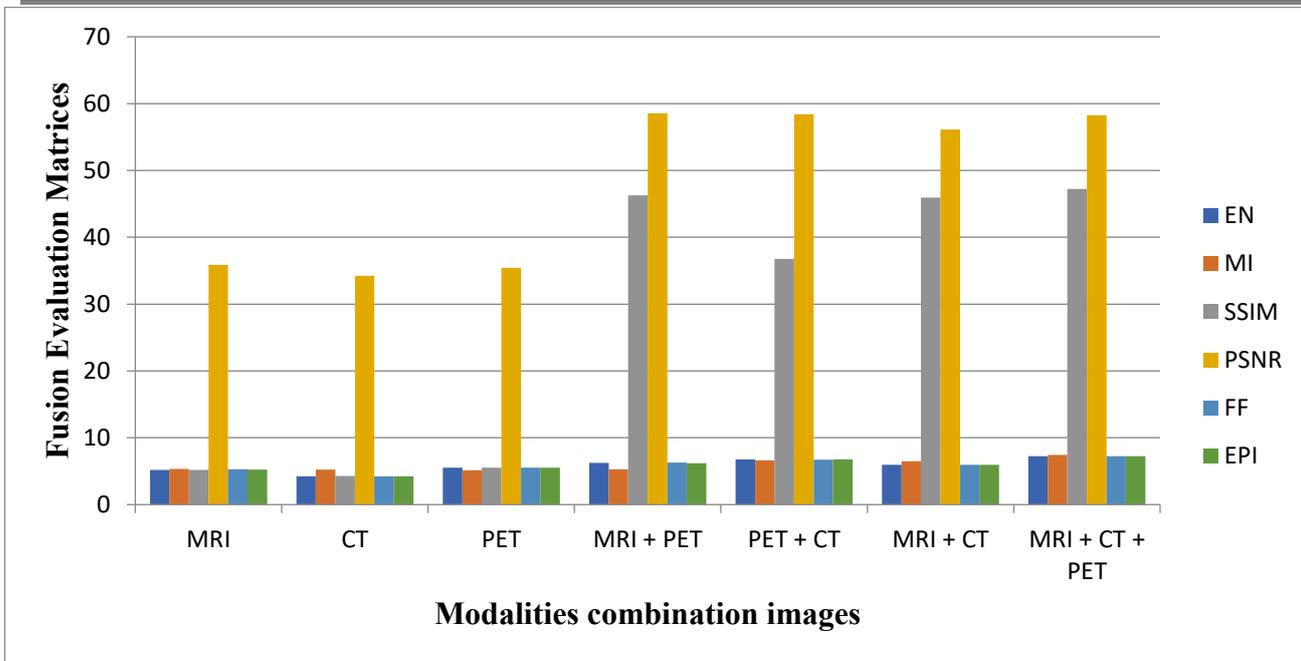
Figure 7: Modality image Combination Evaluation using DCT Fusion

Table 8: Evaluation based on fusion images in Modality Combination and Evaluation Metrics for CM-**DWT** Fusion

Modality Combination	EN	MI	SSIM	PSNR	FF	EPI
MRI	25.24	15.33	5.22	35.87	4.21	5.24
CT	34.25	15.23	4.23	34.23	7.25	4.26
PET	44.54	21.14	5.54	35.44	5.34	5.54
MRI + PET	27.23	22.25	36.25	88.56	6.23	6.27
PET + CT	37.74	16.63	60.74	85.43	6.76	6.75
MRI + CT	48.96	26.46	50.96	89.12	5.96	5.96
MRI + CT + PET	59.24	37.44	70.24	98.34	7.24	7.24
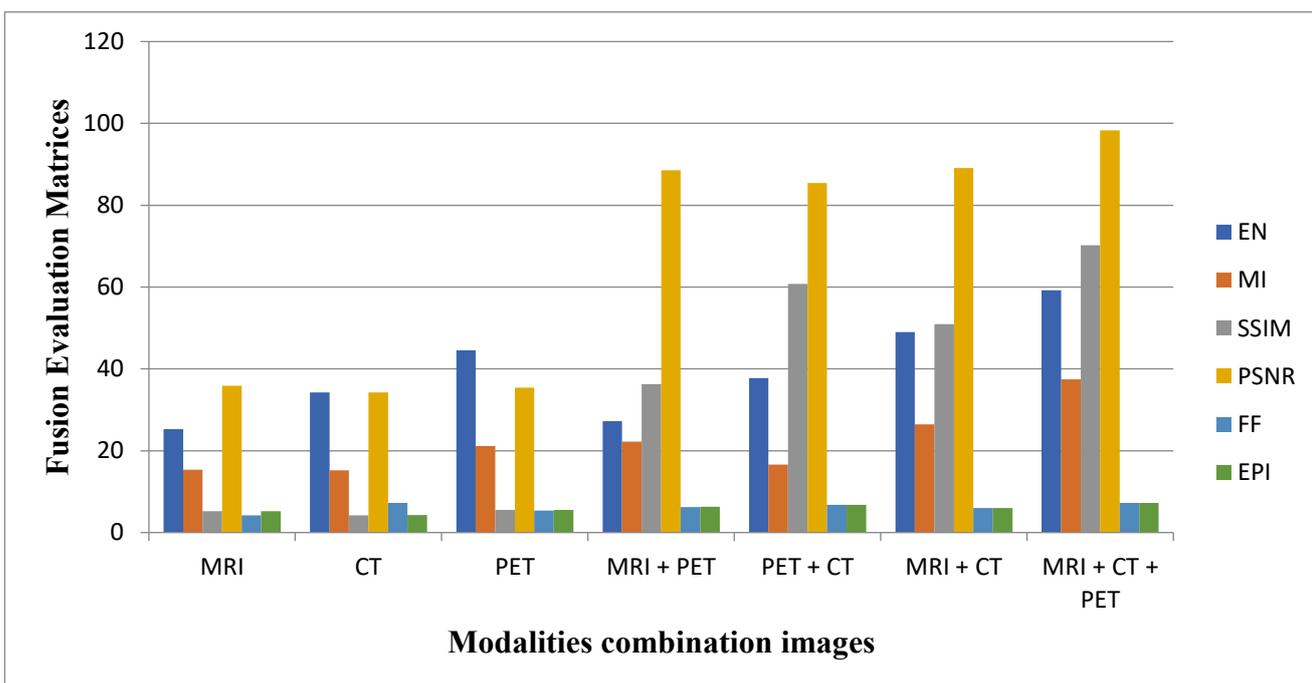
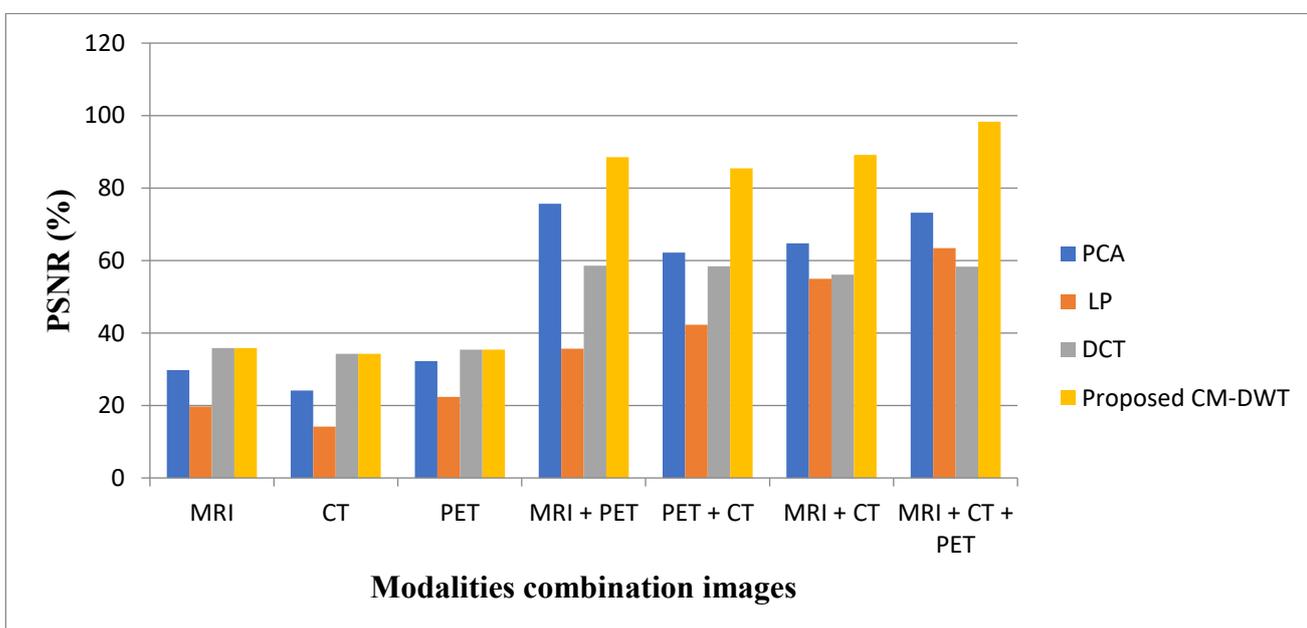**Figure 8:** Modality image Combination Evaluation using CM-DWT Fusion

From **Table 5** to **Table 8** and **Figure 5** to **Figure 8** illustrate that, the findings with higher values across all performance matrices for the envisioning modalities demonstrated the usefulness of these modalities when combined in diverse ways. Combined imaging modalities (such as [MRI, PET], [PET, CT], [MRI, CT], and [MRI, CT, PET]) improve computer vision systems' accuracy, robustness, and dependability. It provides more information, reduces ambiguity and noise, enhances performance under challenging conditions (poor lighting, occlusion, and weather), improves object detection and scene understanding, broadens generalization, and enables better-informed decision-making in real-world applications.

The **PSNR value** of the combined fused images is higher than any of the individual modalities, indicating increased information content and reduced redundancy, which confirm the choice of its usage. The **SSIM** confirms effective integration of complementary information across modalities. The **SSIM** and **PSNR** values demonstrate that structural and visual fidelity were well preserved.

To evaluate the effectiveness of the proposed CM-DWT fusion technique, the researcher uses the combinations of all imaging modality images with higher PSNR (i.e. MRI + CT + PET**,** MRI + CT, PET + CT, MRI + PET); results were compared with three widely used fusion techniques: Principal Component Analysis (PCA)**,** Laplacian Pyramid (LP)**,** and Discrete Cosine Transform (DCT) on the selected fusion performance matrices as shown in **Table 9**. The quality of the fused images across modalities combinations and fusion techniques were quantitatively evaluated using Peak Signal-to-Noise Ratio (PSNR) as shown in **Table 9**. A higher PSNR value indicates better image fidelity and reduced noise after fusion.

Table 9: PSNR values according to modality image combination using Fusion Techniques

Modality Combination	PCA	LP	DCT	Proposed CM-DWT
MRI	29.73	19.73	35.87	35.87
CT	24.11	14.15	34.23	34.23
PET	32.22	22.34	35.44	35.44
MRI + PET	75.67	35.65	58.56	88.56
PET + CT	62.21	42.24	58.43	85.43
MRI + CT	64.77	54.92	56.12	89.12
MRI + CT + PET	73.21	63.44	58.27	98.34

Figure 9: PSNR values according to modality image combination using fusion techniques

The MRI + CT + PET fused images achieved the highest PSNR value (98.34), followed by MRI + CT with value of (89.12), PET + CT with value of (85.56) and lastly MRI + PET with value of (88.56) indicating superior image quality and effective fusion of both anatomical and functional information; suggesting that these modalities are highly complementary in structure and contrast information.

Table 9 above is evident that the proposed CM-DWT-based method consistently outperformed other techniques in all metrics. The PSNR value of the fused images in CM-DWT is higher than most of fusion techniques considered, indicating that the CM-DWT fusion image retained more useful information from all three fusion techniques.

Compared with PCA fusion, which often suppresses subtle PET features, and LP fusion, which introduces mild blurring, the CM-DWT approach produced clearer and more diagnostically relevant images. DCT fusion achieved good sharpness but was limited by spectral inconsistencies. The multi-resolution capability of the CM-DWT enables a more balanced combination of spatial and spectral features, resulting in higher overall fidelity.

These quantitative findings confirm that CM-DWT effectively combines features across modalities producing images with high visual quality and rich diagnostic content suitable for deep learning-based tumor detection.

CONCLUSION

This work presented a novel combinatorial multimodal brain image fusion framework based on the Discrete Wavelet Transform (DWT) to enhance accuracy in neurological image analysis. By effectively integrating complementary structural and functional information from heterogeneous imaging modalities such as MRI, CT, and PET, the proposed method addresses key challenges associated with variations in contrast, spatial resolution, and noise. The use of combinatorial modality analysis, along with multi-resolution wavelet decomposition, enables efficient extraction and fusion of both low- and high-activity regions, ensuring improved preservation of anatomical structures and enhancement of functional details.

The four-level DWT decomposition, combined with adaptive fusion rules, allows the proposed framework to capture fine details and salient features across different scales. The experimental results demonstrate that the Daubechies (db4) wavelet provides optimal performance for multimodal fusion. Quantitative evaluation using standard fusion metrics including Entropy (EN), Mutual Information (MI), Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), Fusion Factor (FF), and Edge Preservation Index (EPI) confirms that the proposed approach consistently outperforms other fusion techniques such as PCA, Laplacian Pyramid, and DCT methods.

Furthermore, the fused images generated by the proposed framework exhibit superior clarity, contrast, and edge preservation, leading to enhanced visual interpretability and diagnostic utility. The achieved fusion accuracy of 98.34% highlights the robustness and effectiveness of the method in combining multimodal brain imaging data. Overall, the results validate that the proposed DWT-based combinatorial fusion approach significantly improves image quality and information content, making it a promising tool for clinical decision support in neurological diagnosis. Future work may focus on extending the framework to deep learning based fusion strategies, real-time implementation, and evaluation on larger and more diverse clinical datasets.

RECOMMENDATION

Based on the outcomes of this study, the following recommendations are proposed to further enhance and extend the applicability of the presented multimodal brain image fusion framework:

i.   Evaluation on Larger and Diverse Datasets

   The proposed method should be validated on larger, multi-institutional datasets with diverse patient populations and pathological conditions to assess its generalizability and clinical reliability.

ii.   Extension to Additional Imaging Modalities

Incorporating other neuroimaging modalities, such as fMRI, DTI, or SPECT, and generation possible combination on them, may provide richer functional and connectivity information, thereby enhancing diagnostic insights.

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Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

REFERENCES

1. Alanazi,M. F., Ali,M. U., Hussain, S. J., Zafar, A.,Mohatram,M., Irfan,M., et al. (2022). Brain tumor/mass classification framework using magnetic-resonance imaging- based isolated and developed transfer deep-learning model. Sensors 22,372. doi: 10.3390/s22010372
2. Abdulkareem, M. B. (2018). Design and development of multimodal medical image fusion using discrete wavelet transform. In 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT) (pp. 1629-1633). IEEE.
3. Alemu, B. S., Feisso, S., Mohammed, E. A., & Salau, A. O. (2023). Magnetic resonance imaging-based brain tumor image classification performance enhancement. Scientific African, 22, e01963.
4. Alsaif, H., Guesmi, R., Alshammari, B. M., Hamrouni, T., Guesmi, T., Alzamil, A., et al. (2022). A novel data augmentation-based brain tumor detection using convolutional neural network. Appl. Sci. 12, 3773. doi: 10.3390/app12083773
5. Alzahrani, A. A. (2024). Enhanced multimodal medical image fusion via modified DWT with arithmetic optimization algorithm. Scientific Reports, 14(1), 19261.
6. Azam, M. A., Khan, K. B., Salahuddin, S., Rehman, E., Khan, S. A., Khan, M. A., ... & Gandomi, A. H. (2022). A review on multimodal medical image fusion: Compendious analysis of medical modalities, multimodal databases, fusion techniques and quality metrics. Computers in biology and medicine, 144, 105253.
7. Azeez, O., & Abdulazeez, A. (2025). Classification of Brain Tumor based on Machine Learning Algorithms: A Review. Journal of Applied Science and Technology Trends, 6(1), 01-15.
8. Sridevi, S. (2021). Image Fusion Algorithm for Medical images using DWT and SR. In 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS) (pp. 853-858). IEEE.
9. Bekhet, S., Hassaballah, M., Kenk, M. A., and Hameed, M. A. (2020). "An artificial intelligence based technique for COVID-19 diagnosis from chest x-ray," in 2020 2nd Novel Intelligent and Leading Emerging Sciences Conference (NILES) (Giza: IEEE), 191–195.
10. Fahmi, F., Apriyulida, F., Nasution, I. K., et al. (2020). Automatic detection of brain tumor on computed tomography images for patients in the intensive care unit. J. Healthc Eng. 2020, 2483285. doi: 10.1155/2020/2483285
11. Zebari, N. A., Mohammed, C. N., Zebari, D. A., Mohammed, M. A., Zeebaree, D. Q., Marhoon, H. A., ... & Martinek, R. (2024). A deep learning fusion model for accurate classification of brain tumours in Magnetic Resonance images. CAAI Transactions on Intelligence Technology, 9(4), 790-804.
12. Hossain, E., Hossain, M. S., Hossain, M. S., Al Jannat, S., Huda, M., Alsharif, S., ... & Rashed, A. N. Z. (2022). Brain Tumor Auto-Segmentation on Multimodal Imaging Modalities Using Deep Neural Network. Computers, Materials & Continua, 72(3).
13. Huang Z., Li Y., Zhao T., Ying P., Fan Y., and Li J. (2021). Infusion port level detection for intravenous infusion based on YOLO v3 neural network. Math. Biosciences Eng., vol. 18, no. 4, pp. 3491–3501, doi: 10.3934/mbe.2021175.
14. Huang, B., Yang, F., Yin, M., Mo, X., & Zhong, C. (2020). A review of multimodal medical image fusion techniques. Computational and mathematical methods in medicine, 2020(1), 8279342.
15. Huang, S. C., Pareek, A., Seyyedi, S., Banerjee, I., & Lungren, M. P. (2020). Fusion of medical imaging and electronic health records using deep learning: a systematic review and implementation guidelines. NPJ digital medicine, 3(1), 136.

16. Huang, X., Sun, J., Gupta, K., Montesano, G., Crabb, D. P., Garway-Heath, D. F., ... & Yousefi, S. (2022). Detecting glaucoma from multi-modal data using probabilistic deep learning. Frontiers in medicine, 9, 923096.

17. Noor, A., Gaffar, S., Hassan, M. T., Junaid, M., Mir, A., & Kaur, A. (2020). Hybrid image fusion method based on discrete wavelet transform (DWT), principal component analysis (PCA) and guided filter. In 2020 First International Conference of Smart Systems and Emerging Technologies (SMARTTECH) (pp. 138-143). IEEE.

18. Zhou, Y., Yang, X., Liu, S., & Yin, J. (2024). Multimodal medical image fusion network based on target information enhancement. IEEE Access, 12, 70851-70869.

19. Jiang, S., Gu, Y., & Kumar, E. (2023). Magnetic resonance imaging (mri) brain tumor image classification based on five machine learning algorithms. Cloud Computing and Data Science, 122-133.

20. Kaur, H., Koundal, D., & Kadyan, V. (2021). Image fusion techniques: a survey. Archives of computational methods in Engineering, 28(7), 4425-4447.

21. Li, Y., Daho, M. E. H., Conze, P. H., Zeghlache, R., Le Boité, H., Tadayoni, R., ... & Quellec, G. (2024). A review of deep learning-based information fusion techniques for multimodal medical image classification. Computers in Biology and Medicine, 108635.

22. Mahdi, M. A., Ahamad, S., Saad, S. A., Dafhalla, A., Qureshi, R., & Alqushaibi, A. (2024). Weighted Fusion Transformer for Dual PET/CT Head and Neck Tumor Segmentation. IEEE Access.

23. Moghtaderi, S., Einlou, M., Wahid, K. A., & Lukong, K. E. (2024). Advancing multimodal medical image fusion: an adaptive image decomposition approach based on multilevel Guided filtering. Royal Society Open Science, 11(4), rsos-231762.

24. Mubashar, A., Asghar, K., Javed, A. R., Rizwan, M., Srivastava, G., Gadekallu, T. R., et al. (2022). Storage and proximity management for centralized personal health records using an ipfs-based optimization algorithm. J. Circ. Syst. Comput. 31, 2250010. doi: 10.1142/S0218126622500104

25. Ramaraj, V., Swamy, M. V. A., & Sankar, M. K. (2024). Medical Image Fusion for Brain Tumor Diagnosis Using Effective Discrete Wavelet Transform Methods. Journal of Information Systems Engineering & Business Intelligence, 10(1).

26. Rathod, R., and Khan, R. A. H. (2021). Brain tumor detection using deep neural network and machine learning algorithm. PalArchs J. Archaeol. Egypt Egyptol. 18, 1085–1093. Available online at: https://archives.palarch.nl/index.php/jae/article/view/8814

27. Raghuram, B., & Hanumanthu, B. (2023). Brain tumor image identification and classification on the internet of medical things using deep learning. Measurement: Sensors, 30, 100905.

28. Senan, E. M., Jadhav, M. E., Rassem, T. H., Aljaloud, A. S., Mohammed, B. A., and Al Mekhlafi, Z. G. (2022). Early diagnosis of brain tumour mri images using hybrid techniques between deep and machine learning. Comput. Math. Methods Med. 2022, 8330833. doi: 10.1155/2022/8330833

29. Srikanth, M. V., Kethavath, S., Yerram, S., Kalli, S., & Naik, J. B. (2024). Brain Tumor Detection through Image Fusion Using Cross Guided Filter and Convolutional Neural Network. ECTI Transactions on Computer and Information Technology (ECTI-CIT), 18(4), 579-590.

30. Sun, M., Zhu, X., Niu, Y., Li, Y., & Wen, M. (2024). Multi-modal Medical Image Fusion Approach Utilizing Gradient Domain Guided Image Filtering. Current Medical Imaging, 20(1), e15734056325441.

31. Usha, M. P., Kannan, G., & Ramamoorthy, M. (2024). Multimodal Brain Tumor Classification Using Convolutional Tumnet Architecture. Behavioural Neurology, 2024(1), 4678554.

32. Vankdothu, R., & Hameed, M. A. (2022). Brain tumor MRI images identification and classification based on the recurrent convolutional neural network. Measurement: Sensors, 24, 100412.

33. Wang, S., Celebi, M. E., Zhang, Y. D., Yu, X., Lu, S., Yao, X., ... & Tyukin, I. (2021). Advances in data preprocessing for biomedical data fusion: An overview of the methods, challenges, and prospects. Information Fusion, 76, 376-421.

34. Weng, Y., Wu, J., Kelly, T., & Johnson, W. (2024). Comprehensive overview of artificial intelligence applications in modern industries. arXiv preprint arXiv:2409.13059.

35. Wu, D., Wang, Y., Wang, H., Wang, F., & Gao, G. (2024). DCFNet: Infrared and visible image fusion network based on discrete wavelet transform and convolutional neural network. Sensors, 24(13), 4065.