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Comparative Analysis of Brain Tumor Classification Using CT, MRI, and Fusion of CT and MRI Images with GLCM Features

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Abstract*:* Classifying brain tumors is essential for efficient diagnosis and therapy planning. The categorization of brain tumors using computed tomography (CT), magnetic resonance imaging (MRI), and fusion of CT and MRI images is compared in this study. In order to capture the unique properties of brain tumors, the study focuses on texture-based feature extraction techniques, such as Gray-Level Co-occurrence Matrix (GLCM), First-Order Statistics (FOS), and Local Binary Patterns (LBP). The classification models are trained and assessed using a dataset of fusion, CT, and MRI images of brain tumors. The tumors are classified using Support Vector Machine (SVM) on the basis of the features that were extracted. The classification results are assessed using performance metrics such area under the curve (AUC), sensitivity, specificity, and accuracy. The experimental results demonstrate that the fusion of CT and MRI images with texture-based features outperforms individual modalities in terms of classification accuracy. The study also provides insights into the importance of feature selection and classifier optimization in improving the classification performance. Overall, the proposed approach shows promising results for accurate and reliable brain tumor classification, which is essential for enhancing patient care and treatment outcomes.

Keywords: *Brain Tumor Analysis, Computed Tomography (CT) Image, Gray-Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP), Magnetic Resonance Imaging (MRI)*

1. Introduction

Brain tumors are among the most challenging conditions in modern healthcare, requiring accurate and timely diagnosis for effective treatment planning. Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are the two most commonly used imaging modalities for brain tumor identification and classification. Each modality has its advantages and limitations, making them complementary in clinical practice. CT provides excellent spatial resolution and is particularly useful for detecting calcifications and acute hemorrhages, while MRI offers superior soft tissue contrast, making it ideal for visualizing brain tumors and their relationship with surrounding tissues [1].

In recent years, there has been a growing interest in combining CT and MRI images to scale up the accuracy of brain tumor classification. Image fusion techniques aim to integrate the complementary information from both modalities to enhance the overall diagnostic performance. Moreover, the development of modern image analysis methods, such as GLCM, FOS, and Local Binary Pattern (LBP) features, has further enriched the diagnostic capabilities of medical imaging [2].

The fusion of CT and MRI images has emerged as a critical technique in medical imaging, particularly for brain tumor classification. CT provides high spatial resolution and is useful for highlighting calcifications and bony structures, while MRI offers superior soft tissue contrast, making it ideal for visualizing tumors and surrounding tissues. By combining these modalities, clinicians can obtain a more comprehensive view of the tumor, enabling more accurate diagnosis and treatment planning. However, the challenge lies in effectively integrating information from both modalities to improve classification accuracy [3]. Before fusion, the images from two modalities may also be preprocessed for denoising [15], to remove any noise present in the raw data using denoising techniques [21][24].

To address this challenge, researchers have proposed various feature extraction methods, such as GLCM, FOS, and LBP. GLCM captures spatial relationships of pixel intensities, FOS computes basic statistical measures of image intensities, and LBP describes the local texture patterns within an image. By extracting these features from fused CT and MRI images, researchers aim to capture both the structural and textural information necessary for accurate tumor classification. This approach allows for more robust feature representation, enhancing the performance of machine learning algorithms used for classification tasks. The fusion of CT and MRI images with these feature extraction methods thus holds great promise for improving the accuracy and reliability of brain tumor classification in clinical settings. This article presents a comprehensive comparative analysis of brain tumor classification using CT, MRI, and CT-MRI fused images. The study evaluates the performance of these modalities and features in distinguishing between different types of brain tumors. The results highlight the strengths and weaknesses of each approach, providing valuable insights for clinical decision-making [4].

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The remainder of this article is organized as follows: Section 2 provides an overview of the related work in brain tumor classification using medical imaging and feature extraction techniques. Section 3 describes the materials and methods used in this study, including the dataset, image preprocessing, feature extraction, and classification algorithms. Section 4 presents the experimental results and discussions, followed by conclusions and future research directions in Section 5.

2. Literature Review

Brain tumor classification is a critical task in medical imaging analysis, crucial for accurate diagnosis and treatment planning. CT and MRI are among the most common imaging modalities used for brain tumor diagnosis because of their ability to provide detailed structural information. However, each modality has its limitations with respect to sensitivity and specificity. The fusion of CT and MRI images has been proposed as a technique to overcome these limitations by combining the complementary information provided by each modality. In recent years, texture features extracted using the GLCM have given advantageous results in image analysis tasks, including brain tumor classification. Support Vector Machine (SVM) is a widely used classification algorithm known for its ability to handle high-dimensional data and nonlinear classification problems, making it suitable for the complex nature of medical image data. This literature survey aims to review the current state-of-the-art techniques and challenges in brain tumor classification using CT, MRI, and the fusion of CT and MRI images with GLCM features by SVM-based classification [5] and combination of deep learning and machine learning based classification [23].

2.1. Brain Tumor Identification

The goal of identifying brain tumor is to categorize the given image pattern into one of the several predefined classes. An intelligent and accurate brain tumor classification can assist the doctor to make a proper decision about the treatment of the patient. As a means to the end, feature extraction and selection in the medical images has become a critical step in developing the diagnostic tools [6]. Feature selection has several practical advantages in real-world data and in the applications of automatic pattern recognition in medical images. High-dimensional feature spaces have inherent problems due to limited access to medical data across different clinical sites. Feature selection has the potential to improve classification accuracy, reduce the amount of time and the number of samples required for diagnosis, and improve the understanding of the process of image classification by identifying which features are most important. Feature selection also plays a vital role in constructing the real-time diagnostic tool for image-guided therapy. High computational performance is required to segment, register, and classify medical images [7-10].

2.2. CT Imaging and its Role in Brain Tumor Classification

CT imaging uses X-rays to produce images of the human body. Due to its low cost and very high speed, it is widely used in the diagnosis and evaluation of many medical conditions. CT images are obtained from the axial slices of the brain from which the resulting 2-D images can show great detail of the anatomy of the brain. Good accessibility to the brain structures has made CT a preliminary method for brain tumor diagnosis and treatment planning. Usually, to increase the visibility of certain features, post-image processing with filtration, edge enhancement, and contrast enhancement are performed [11].

Brain CT images provide visualization of the anatomical details in the brain, including the ventricles, the inner and outer tables of the skull, and the cerebrospinal fluid surrounding these structures. Some types of shifts in the anatomic locations are caused by intracranial tumor mass effect, which creates distortion and displacement of the normal brain structures. These can be visualized on the CT images. The extent of the distortion can indicate the likely degree of success of surgical operation to remove the tumor. Moreover, the type of the tumor can sometimes be classified by the difference in image intensity among the tumor and its surrounding edema and the specific location of the tumor in the brain. These features of CT imaging offer great potential in the automation of brain tumor classification [12].

2.3. MRI Imaging and its Role in Brain Tumor Classification

Though MRI has been proven superior to CT in the definition of normal anatomical brain MRI plays a crucial role in the non-invasive diagnosis and classification of brain tumors, offering high-resolution images that aid in tumor detection, localization, and characterization. Various MRI techniques, including T1-weighted, T2-weighted, and contrast-enhanced MRI, provide complementary information about tumor morphology, tissue composition, and vascularization, essential for accurate classification [13]. Image post-processing methods such as texture analysis, diffusion-weighted imaging, and perfusion imaging further enhance diagnostic accuracy by quantifying tumor heterogeneity, cellularity, and microvascularization. Machine learning and deep learning algorithms have been extensively employed to automate tumor classification based on MRI features, achieving high accuracy and reducing the burden on radiologists. Despite these advancements, challenges remain, including the standardization of imaging protocols, the integration of multi-modal imaging data, and the development of robust classification models for different tumor types and grades [14]. Future research directions include the incorporation of advanced imaging biomarkers, the exploration of multi-scale imaging approaches, and the integration of MRI with other molecular and genetic markers for comprehensive brain tumor characterization [15].

2.4. Fusion of CT and MRI Images with GLCM Features

The fusion of CT and magnetic resonance imaging MRI images for brain tumor classification offers several advantages. Firstly, the combination of these imaging modalities provides complementary information, enhancing the overall accuracy of tumor detection and classification. CT imaging is adept at highlighting structural details, such as calcifications, while MRI excels in depicting soft tissues and delineating tumor boundaries with high contrast [16]. Secondly, by GLCM features, the fused images can be analyzed in greater detail. GLCM features capture the spatial relationships of pixel intensities, enabling the extraction of texture information that can be crucial for distinguishing between different tumor types or tumor regions. Thirdly, the fusion of CT and MRI images with GLCM features can improve the sensitivity and specificity of brain tumor classification algorithms. The combination of these modalities and features can lead to more robust and reliable diagnostic tools, aiding clinicians in making more accurate and timely treatment decisions for patients with brain tumors. Overall, the fusion of CT and MRI images with GLCM features represents a promising approach for enhancing brain tumor classification, offering improved diagnostic capabilities and potentially leading to better patient outcomes [17].

3. Methodology

The pictorial representation of formulated methodology is as shown in the Fig. 3.1. The dataset consists of 40 CT and 40 MRI images out of which 30% images indicate malignant tumors and remaining 70% are benign. Initially the CT and MRI images are considered individually and the classification performance is analyzed.

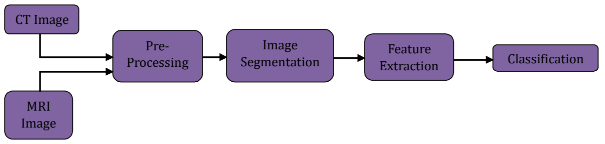


Fig. 3.1 Proposed block diagram of brain tumor image classification methodology utilizing both CT and MRI Images

To utilize the advantages of both CT and MRI images the image fusion is carried out and the further steps for classification is as explained below:

- Combined CT and MRI Image Fusion: The process starts with acquiring both CT (Computed Tomography) and MRI (Magnetic Resonance Imaging) images of the brain. Since CT provides structural information and MRI provides detailed soft tissue information, combining these modalities can enhance the accuracy of tumor detection. Fusion technique used is bi-level Stationary Wavelet Transform [22] with maximum fusion rule to merge these images into a single, more informative image.
- Preprocessing: The fused image undergoes preprocessing to enhance its quality and prepare it for segmentation. Preprocessing steps include noise removal, intensity normalization, and image enhancement techniques.
- Image Segmentation: Segmentation is the process of dividing the image into multiple regions or segments based on certain characteristics. In brain tumor classification, segmentation is crucial for isolating the tumor region from the rest of the brain. Techniques like thresholding, region growing, or clustering can be used for this purpose.
- GLCM Feature Extraction: After segmentation, Gray Level Co-occurrence Matrix (GLCM) features are extracted from the tumor region. GLCM is a statistical method that captures the spatial relationship of pixel intensities. Features like contrast, correlation, energy, and homogeneity can be computed from GLCM.
- Classification using SVM: The extracted GLCM features are fed into a Support Vector Machine (SVM) classifier for tumor classification. SVM is a supervised machine learning algorithm that finds the optimal hyperplane to separate different classes. In this case, SVM is trained on a dataset of labeled tumor images to learn the characteristics of tumor and non-tumor regions.

The entire process, from image fusion to classification, forms a pipeline for accurate brain tumor classification. Each block plays a crucial role in improving the overall performance of the system.

3.1. GLCM Features, FOS Features and LBP Features

GLCM (Gray-Level Co-occurrence Matrix) features are statistical measures derived from the GLCM, which is a matrix that describes how often different combinations of pixel intensity values occur in an image. GLCM features are commonly used in image processing and texture analysis to characterize the spatial relationships in an image [18]. The common GLCM features are,

• Mean: The mean of the GLCM is the average value of the matrix elements and represents the average gray-level value for the co-occurring pixel pairs. It provides an indication of the overall intensity of the image texture.

$$\mu_i = \sum_{i,j=0}^{N-1} i\left(P_{i,j}\right)$$

$$\mu_j = \sum_{i,j=0}^{N-1} j\left(P_{i,j}\right)$$

Where $P_{i,j}$ is the co-occurrence matrix, μ_i is the mean of ith row μj is the mean of jth column.

- Variance: The variance of the GLCM measures the spread of the values around the mean. It indicates the level of variation or texture irregularity in the image.

$$\sigma_i^2 = \sum_{i,j=0}^{N-1} P_{i,j}(i-\mu_i)^2$$

$$\sigma_j^2 = \sum_{i,j=0}^{N-1} P_{i,j}\left(j-\mu_j\right)^2$$

• GLCM Constant (Angular Second Moment): Also known as angular second moment or energy, this feature measures the homogeneity of the image texture. It is calculated as the sum of the squared elements in the GLCM and represents the orderliness or uniformity of the texture.

$$\text{Con} = \sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$$

• Homogeneity: Homogeneity is a measure of the closeness of the distribution of elements in the GLCM to the GLCM diagonal. It indicates the level of local uniformity or smoothness in the image texture.

$$\text{Hom} = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$$

• Correlation: Correlation measures the linear dependency between the gray-level values of pixel pairs in the image. It indicates the level of correlation or similarity between the pixel pairs in terms of their gray-level values.

$$\text{Cor} = \sum_{ij=0}^{N-1} P_{i,j}\left[\frac{(i-\mu_i)\left(j-\mu_j\right)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right]$$

• Cluster Shade: Cluster shade is a measure of the skewness of the GLCM. It quantifies the asymmetry of the GLCM distribution and provides information about the texture complexity.

$$\text{Shd} = \sum_{i,j=0}^{N-1} \left\{i+j-\mu_i-\mu_j\right\}^3 P_{ij}$$

These features are commonly used in texture analysis to characterize and differentiate textures in images.

First-order statistics in the context of data analysis and statistics refer to basic metrics that summarize the distribution of a dataset. Two common first-order statistics are skewness and kurtosis.

• Skewness: Skewness measures the asymmetry of the probability distribution of a real-valued random variable about its mean. A distribution is considered skewed if it is not symmetrical (i.e., it does not look the same on both sides of the mean).

$$S = \frac{E(x-\mu)^3}{\sigma^3}$$

• Kurtosis: Kurtosis measures the "tailedness" of the probability distribution of a real-valued random variable. It describes the shape of the distribution's tails in relation to its peak (or mode). Both skewness and kurtosis are important in understanding the shape and behavior of data distributions.

$$k = \frac{E(x-\mu)^4}{\sigma^4}$$

Local Binary Patterns (LBP) is a powerful texture descriptor widely used in image analysis and computer vision tasks, including brain tumor image classification. LBP encodes the local structure of an image by comparing each pixel with its neighboring pixels. It is particularly useful for capturing the texture patterns present in medical images like MRI scans [18]. In the context of brain tumor classification, LBP can be applied to extract texture features from the tumor region, which can then be used as input to a machine learning model for classification. This approach is effective because tumors often exhibit distinct texture patterns that can be discriminated using LBP. Furthermore, LBP is computationally efficient and robust to noise, making it suitable for analyzing medical images. Overall, LBP is a valuable tool for extracting meaningful features from brain tumor images, aiding in the accurate classification and diagnosis of brain tumors.

3.3. SVM Classification Algorithm

Support Vector Machine (SVM) is a powerful supervised machine learning algorithm commonly used for classification tasks. When used in combination with features extracted from images, such as GLCM, FOS, and LBP, SVM can be particularly effective for image classification tasks [21].

When using SVM for classification based on GLCM, FOS, and LBP features, the typical workflow involves the following steps:

• Feature Extraction: Extract GLCM, FOS, and LBP features from the input images. This step involves calculating the GLCM matrix, computing first-order statistics, and applying the LBP operator to generate feature vectors for each image.

• Feature Selection: Select the most relevant features from the extracted feature vectors. This step helps reduce the dimensionality of the feature space and improve the classifier's performance.

• Training: Split the dataset into training and testing sets. Use the training set to train the SVM classifier using the selected features. During training, the SVM learns the optimal hyperplane that separates the different classes in the feature space [19].

• Testing: Evaluate the performance of the trained SVM classifier on the testing set. Calculate metrics such as accuracy, sensitivity, specificity, and ROC curve to assess the classifier's performance.

In summary, SVM classification based on GLCM, FOS, and LBP features is a robust approach for image classification tasks, especially in applications where texture information is critical, such as medical image analysis, remote sensing, and object recognition.

3.4. Performance Evaluation Metrics

In the context of SVM classification, sensitivity, specificity, and accuracy are performance metrics used to evaluate the performance of the classifier [20]. Here are the definitions of these metrics:

• Sensitivity (True Positive Rate, Recall): Sensitivity measures the proportion of actual positive cases that are correctly identified by the classifier.

Sensitivity = True Positives / (True Positives + False Negatives)

• Specificity (True Negative Rate): Specificity measures the proportion of actual negative cases that are correctly identified by the classifier.

Specificity = True Negatives / (True Negatives + False Positives)

• Accuracy: Accuracy measures the overall correctness of the classifier across all classes.

Accuracy = (True Positives + True Negatives) / (True Positives + True Negatives + False Positives + False Negatives)

It's essential to note that while sensitivity and specificity primly focus on the performance within individual classes, accuracy gives an overall view of the classifier's performance.

4. Results and Discussions

Multimodal brain tumor image segmentation plays a vital role in the medical trend for early diagnosis and treatment of such abnormality. In this paper, results of tumor classification using CT, MRI, and fused MRI and CT images are presented. Fig. 2, 3, 4 indicate the CT, MRI and Fused images of 10 patients.

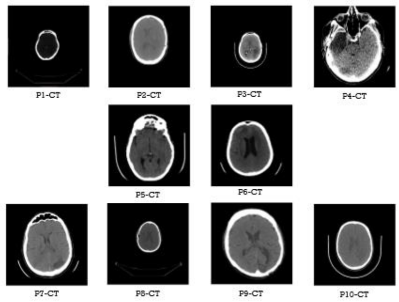


Fig. 2 CT Images of Brain Tumor of patients

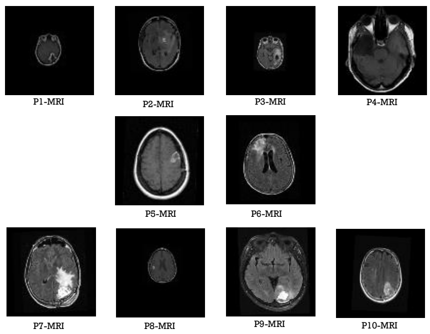


Fig. 3 MRI Images of Brain Tumor of patients

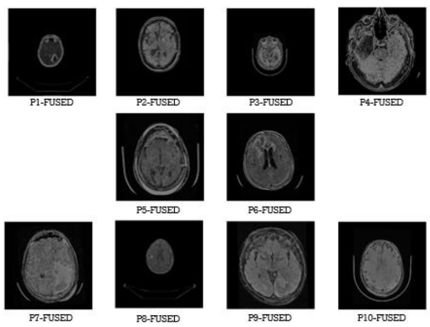


Fig. 4 CT and MRI Fused Images of Brain

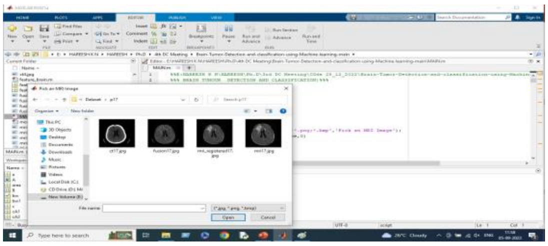


Fig. 3.5 CT Input Image selection in MATLAB 2021a

Fig. 2 and 3 shows the CT and MRI images of ten patients for classification using SVM classifier using GCLM features. The accuracy, sensitivity and specificity for classification using only CT images are poor as indicated in Fig. 9. The CT and MRI fused image input for classification is as shown in Fig. 4. Further, Fig. 6 and 7 shows the outputs in next stages for classification of fused images of brain tumor patients. The sample output of resized image, segmented tumor, detected tumor image, the features selected and the classification outputs are as shown below. The sample image considered indicates a "Malignant Tumor".

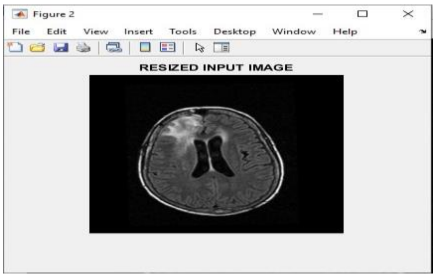


Fig. 6 (a) Input image resized to 256 X 256

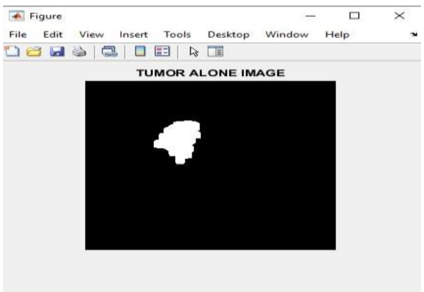
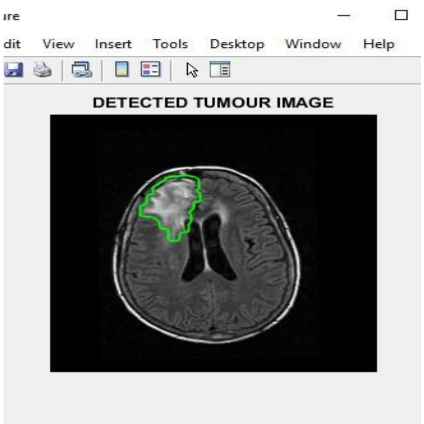
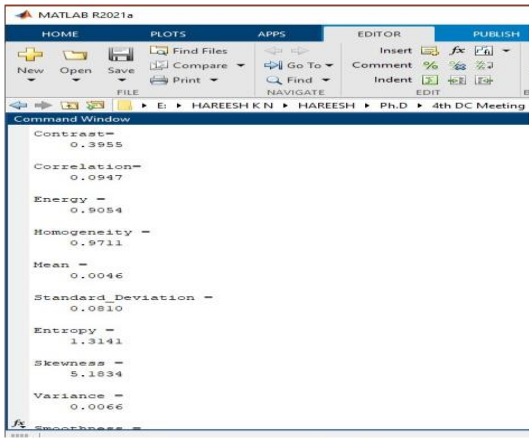


Fig. 6 (b) Segmented Tumor (ROI)



(a)



(b)

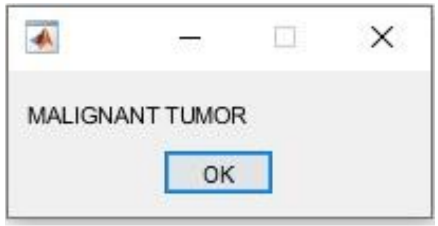
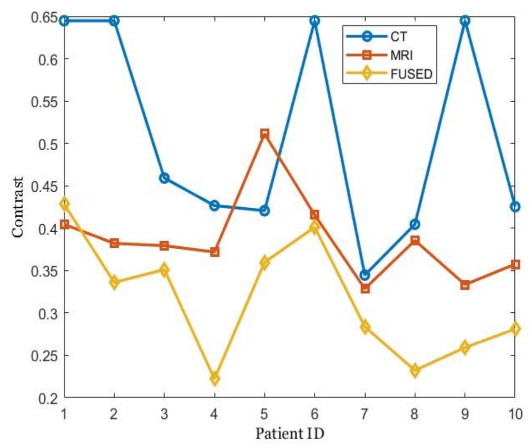
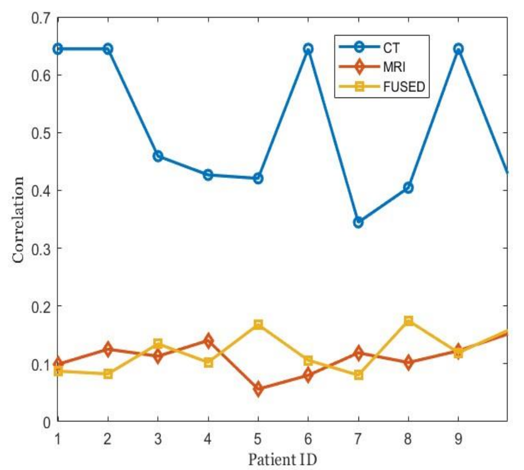


Fig. 7 (a) Boundary of the Segmented Tumor (b) Features Extracted (c) Classification of Output



(a)



(b)

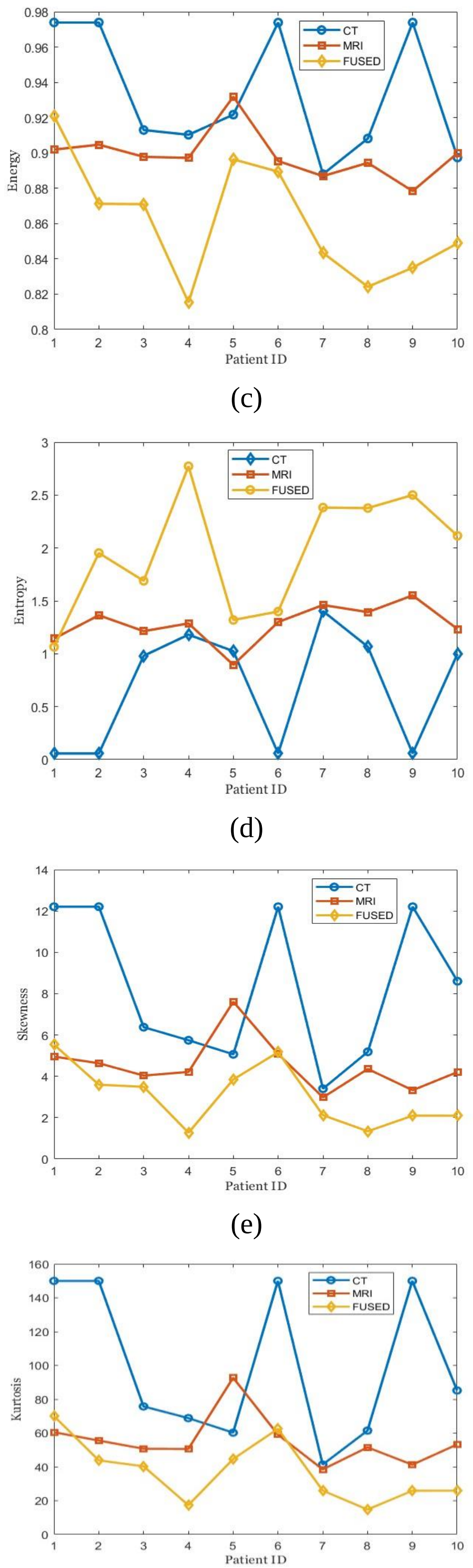


Fig. 8 The plot of Patient ID verses Feature of CT, MRI & Fused images (a) Contrast (b) Correlation (c) Energy (d) Entropy (e) Skewness and (f) Kurtosis

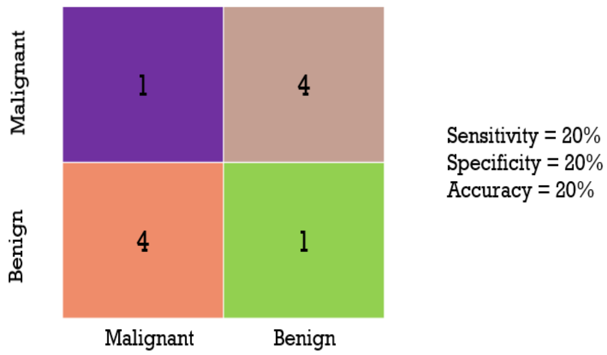


Fig. 9 Confusion matrix for CT images for brain tumor classification

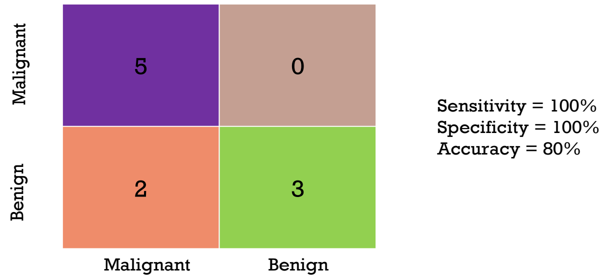


Fig. 10 Confusion matrix for MRI images for brain tumor classification

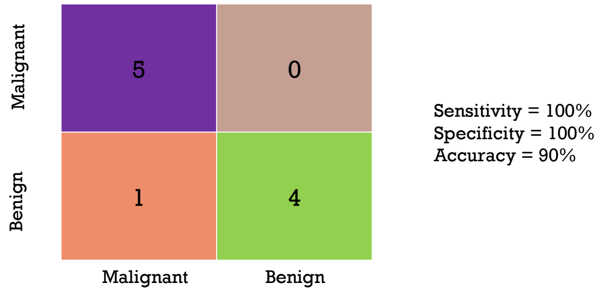


Fig. 11 Confusion matrix for Fused CT and MRI images for brain tumor classification

The Table 1 to Table 3 enumerates the feature vectors of CT, MRI and Fused image for 10 patients. There is a good trade-off between individual images and fused image which are used to classify the tumor with good accuracy. The contrast, correlation, energy, entropy, skewness and kurtosis values for the fused CT and MRI images are as shown in the Fig. 8 along with its plot. Likewise, the values for mean, standard deviation, homogeneity and other GCLM, FOS and LBP feature values and plots are obtained through MATLAB 2021a simulation. The confusion matrices for CT, MRI and fused-images based classification are as shown in Fig. 9 – 10. For fused CT-MRI image inputs, the confusion matrix demonstrates strong performance, showcasing very high accuracy, sensitivity, and specificity in brain tumor image classification. This indicates that the classifier effectively distinguishes between different classes of brain tumors with minimal misclassification. The high accuracy suggests that the majority of predictions are correct, while the elevated sensitivity indicates a low rate of false negatives, meaning that the classifier effectively identifies most positive cases. Additionally, the high specificity indicates a low rate of false positives, indicating that the classifier is adept at correctly identifying negative cases. Overall, these results highlight the robustness and effectiveness of the classifier in accurately classifying brain tumors using fused CT-MRI images when compared to the individual CT and MRI image-based classifications.

Table 1. The GLCM features along with First Ordered Statistics (FOS) and Local Binary Pattern (LBP) extracted from the CT scan image of 10 patients

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Contrast	0.6447	0.6447	0.4592	0.4267	0.4207	0.6447	0.3447	0.4046	0.6447	0.4254
Correlation	-0.0066	-0.0066	0.0787	0.13	0.144	-0.0066	0.1357	0.1406	-0.0066	0.0682
Energy	0.9739	0.9739	0.913	0.9103	0.9217	0.9739	0.888	0.9082	0.9739	0.8974
Homogeneity	0.9885	0.9885	0.973	0.9718	0.9741	0.9885	0.9664	0.9704	0.9885	0.9214
Mean	0.0066	0.0066	0.0044	0.0052	0.0051	0.0066	0.0032	0.0055	0.0066	0.0042
STD	0.0809	0.0809	0.081	0.081	0.081	0.0809	0.0811	0.0809	0.0809	0.0823
Entropy	0.0571	0.0571	0.981	1.1808	1.0247	0.0571	1.403	1.0664	0.0571	0.9987
Skewness	12.2068	12.2068	6.3777	5.7443	5.0649	12.2068	3.4008	5.1849	12.2068	8.6014
Smoothness	0.9737	0.9737	0.9611	0.9669	0.9666	0.9737	0.9472	0.9688	0.9737	0.9568
Kurtosis	150.007	150.0066	75.7571	68.8499	60.2465	150.0066	41.3812	61.4672	150.0066	85.2245

Table 2. The GLCM features along with First Ordered Statistics (FOS) and Local Binary Pattern (LBP) extracted from the MRI scan image of the same 10 patients

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Contrast	0.4046	0.3821	0.3794	0.3719	0.5113	0.4156	0.3286	0.3856	0.3335	0.3576
Correlation	0.0992	0.1252	0.1132	0.1403	0.0563	0.0802	0.119	0.1022	0.1226	0.152
Energy	0.9019	0.9047	0.8978	0.8972	0.9319	0.8954	0.8869	0.8944	0.8784	0.8999
Homogeneity	0.9708	0.9701	0.9683	0.9681	0.9773	0.9678	0.966	0.9673	0.9631	0.969
Mean	0.0049	0.0045	0.0034	0.0046	0.0057	0.0049	0.0032	0.0043	0.0039	0.0045
STD	0.081	0.081	0.081	0.081	0.0809	0.081	0.0811	0.081	0.081	0.081
Entropy	1.1436	1.3637	1.2134	1.287	0.8949	1.3001	1.4609	1.3936	1.5518	1.2335
Skewness	4.9528	4.6326	4.0351	4.2121	7.6089	5.0768	2.9805	4.3548	3.3263	4.2045
Smoothness	0.9651	0.9619	0.9506	0.9631	0.9697	0.9651	0.9479	0.96	0.956	0.9624
Kurtosis	60.5045	55.5665	50.7214	50.6089	92.7404	59.1022	38.4995	51.5381	41.2886	53.2594

Table 3. The GLCM features along with First Ordered Statistics (FOS) and Local Binary Pattern (LBP) extracted from the CT-MRI Fused image of the same 10 patient. * Standard Deviation

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Contrast	0.4284	0.3361	0.3512	0.2222	0.3598	0.4013	0.2838	0.2323	0.2593	0.2811
Correlation	0.0873	0.0826	0.1345	0.1026	0.1677	0.1061	0.0805	0.1746	0.1192	0.1584
Energy	0.921	0.8712	0.871	0.8153	0.8964	0.8894	0.8434	0.8242	0.835	0.8488
Homogeneity	0.9751	0.9633	0.9619	0.9491	0.9679	0.967	0.9558	0.9493	0.9539	0.9567
Mean	0.0045	0.0032	0.0049	0.0025	0.0046	0.0051	0.0031	0.0035	0.0029	0.0042
STD*	0.081	0.0811	0.081	0.0811	0.081	0.081	0.0811	0.081	0.0811	0.081
Entropy	1.0645	1.9523	1.6892	2.7726	1.3193	1.399	2.3822	2.3769	2.5009	2.115
Skewness	5.5326	3.5933	3.4912	1.2699	3.8511	5.1689	2.1184	1.3405	2.0963	2.0935
Smoothness	0.9617	0.9476	0.9648	0.9327	0.9631	0.966	0.9464	0.9511	0.9418	0.959
Kurtosis	70.054	43.8409	40.3492	17.3544	44.635	62.516	25.9766	14.7735	25.887	25.9785

5. Conclusion

In conclusion, our study presents a comprehensive comparative analysis of brain tumor classification using CT, MRI, and fused CT-MRI images with GLCM, FOS, and LBP features. Our findings reveal that the fusion of CT and MRI images significantly improves the classification performance, showcasing superior accuracy, sensitivity, and specificity compared to individual modalities. The fused images provide complementary information that enhances the classifier's ability to distinguish between different tumor types. This highlights the potential of fused CT-

MRI images in improving the diagnostic accuracy of brain tumor classification systems. Our results underscore the importance of multimodal imaging and feature fusion techniques in advancing the field of medical image analysis, particularly in the context of brain tumor classification.

The future scope of the study lies in further refining the classification model by exploring advanced feature extraction techniques and machine learning algorithms. Additionally, incorporating deep learning models, such as convolutional neural networks (CNNs), could enhance the classification performance, especially for complex tumor patterns. Furthermore, expanding the dataset to include a broader range of tumor types and sizes would improve the model's generalizability. Integration of other imaging modalities, such as PET and SPECT, could also be explored to capture additional tumor characteristics.

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