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Multimodal Fusion Techniques for Integrated Biomedical Imaging

V Rajesh[1], B Rakesh Babu[1], Sk Hasane Ahammad[1], Mohammed R. Hayal[2], Ebrahim E. Elsayed[2]

[1]Department of Electronics and Communication Engineering, Koneru Lakshmaiah Education Foundation. Vaddeswaram, Guntur, India.
[2]Department of ECE, Faculty of Engineering, Mansoura University, Mansoura, Egypt.

***Corresponding author:** Ebrahim E. Elsayed

ABSTRACT

Multimodal biomedical imaging has turned into an essential diagnostic tool, utilizing the full potential of imaging modalities to improve disease analysis. The present work introduces a combined Discrete Wavelet Transform–Principal Component Analysis (DWT–PCA) method for the merging of Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET) scans aimed at acquiring both structural and functional information of brain tumors. The suggested technique employs DWT for frequency-domain decomposition and PCA for statistical feature integration, then image reconstruction and enhancement are done. A fine-tuned ResNet50 network is used to extract deep features for the classification of tumor types. The results of the experimental evaluation show that the fused images get better PSNR (≈ 39 dB), SSIM (≈ 0,97), and classification accuracy (≈ 97,8 %) than unimodal images. The findings support that the DWT–PCA-based multimodal fusion method has benefits in diagnostic quality, visual clarity, and reliability for clinical decision-making in the field of biomedical imaging.

Keywords: Multimodal Biomedical Imaging; MRI-PET Fusion; Discrete Wavelet Transform (DWT); Principal Component Analysis (PCA); Image Enhancement; Deep Learning; ResNet50; Tumor Classification.

INTRODUCTION

Medical imaging has come up to be a very important area of modern healthcare, allowing the non-invasive visualization and diagnosis of the internal body structures. However, one imaging method can never completely reveal the full diagnostic information about an organ's structural and functional features. For example, MRI shows the structure of the organ very clearly, and PET scans reveal live metabolic and chemical activities of the organ. The combination of these techniques is referred to as multimodal biomedical imaging, which provides a comprehensive view of the clinical diagnosis, especially in terms of brain tumor detection and characterization.[1,2] However, despite the big steps taken, there are still difficulties in aligning, combining and enhancing multimodal images without losing some of the key features. The simplest method of fusion at the pixel level often leads to the blurring or the silencing of the diagnostic cues.[3] To deal with these problems, fusion methods that mix spatial and frequency-domain techniques have been proposed. Among them, DWT and PCA have become very good methods for decomposing images while keeping the important features.[4,5]

Automatic and reliable feature extraction along with classification denote the main steps through which deep learning applied medical image to pass or not to pass tests in the daily routine of hospitals. One of the latest studies has shown that excellent capability of detecting and classifying the disease applied classical fusion methods (DWT-PCA) with deep learning tool (ResNet50).[6] The authors of the manuscript that is the subject of this paper, plan to employ the current hybrid fusion path to bring together the MRI and PET modalities, thereby sharpening the diagnosis and increasing the reliability in classification. The work that is suggested is the establishment of a hybrid DWT-PCA-based multimodal fusion framework that would be capable of optimally merging the structural and functional data of the corresponding brain imaging modalities. The fusion technique interlinks MRI with PET, thus producing a complete diagnostic view that incorporates both the anatomical details and the metabolic activity. The deep discriminative features are derived from the fine-tuned ResNet50 network, which in turn allows the automated and very precise classification of tumor types based on the learned spatial and contextual features. The model's performance is assessed quantitatively through the application of the widely used image quality and diagnostic metrics, including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and classification accuracy. The combination of traditional image fusion and modern deep learning provides a powerful basis for the improvement of tumor visualization, the raising of diagnostic reliability, and the expansion of the use of automated medical image analysis in clinical scenarios.

METHOD

The suggested multimodal fusion and classification framework includes four main stages: preprocessing, fusing via DWT–PCA, feature extraction using ResNet50, and tumor classification.

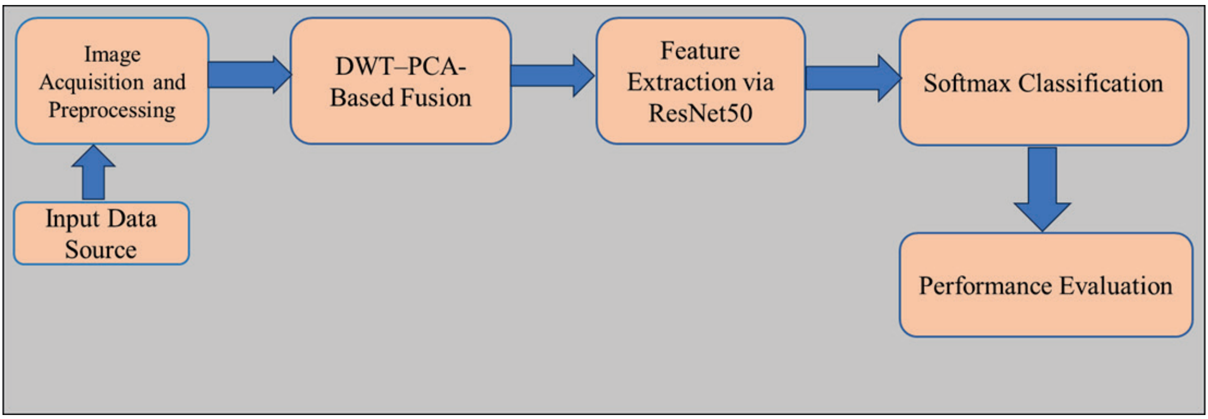

Figure 4.1. Methodology of the Proposed Work

Step 1: Image Acquisition and Preprocessing

MRI and PET brain images were gotten from datasets that are open-access (like the BraTS and Harvard Whole Brain Atlas). Each image was resized to the same size (256 × 256) and then normalized within [0,1]. Registration methods were used to spatially align the two modalities and thus guarantee pixel correspondence between MRI and PET. Gaussian smoothing was used for the reduction of noise in the MRI images, and PET scans were brightness-scaled for uniformity.

Step 2: DWT-PCA-Based Fusion

The pre-processed MRI and PET images underwent Discrete Wavelet Transform (DWT) and were divided into four sub-bands: approximation (LL), horizontal (LH), vertical (HL), and diagonal (HH) components. PCA was subsequently executed on the sub-bands to calculate fusion weights. Low-frequency structural features (from MRI) were combined with high-frequency functional details (from PET) to reconstruct the fused image. This method preserved anatomical clarity and, at the same time, provided metabolic information that was crucial for tumor evaluation.

Step 3: Feature Extraction via ResNet50

The merged images were passed through a fine-tuned ResNet50 network that had been pre-trained on ImageNet. The hierarchical feature representations were among those extracted by the convolutional layers, and the last fully connected layer was altered for binary or multi-class tumor classification. Transfer learning made a remarkable impact on the training duration by reducing it considerably and at the same time boosting performance on scarce medical data.

Step 4: Classification and Evaluation

A Softmax layer was used for the classification of the extracted features. The performance of the system was measured in terms of Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and classification accuracy. The whole process is illustrated in the block diagram presented in figure 4.1.

RESULTS AND DISCUSSION

The proposed DWT–PCA + ResNet50 fusion model was implemented in MATLAB 2017b (for preprocessing and fusion) and Python (TensorFlow/Keras) (for deep learning classification). Four representative brain tumor cases, including MRI, PET, and fused images, were evaluated. The fused images showed better edge visibility and more details than the individual modalities. The quantitative evaluation metrics shown in Table 1 facilitated the evaluation of fusion quality and classification performance by means of PSNR, SSIM, and overall accuracy.

Table 4.1. Performance Metrics for Multimodal Fusion and Classification

Image Sample	PSNR (dB)	SSIM	Accuracy (%)
Case 1	38,92	0,971	97,6
Case 2	39,45	0,968	97,9
Case 3	38,78	0,974	97,5
Case 4	39,21	0,970	98,1

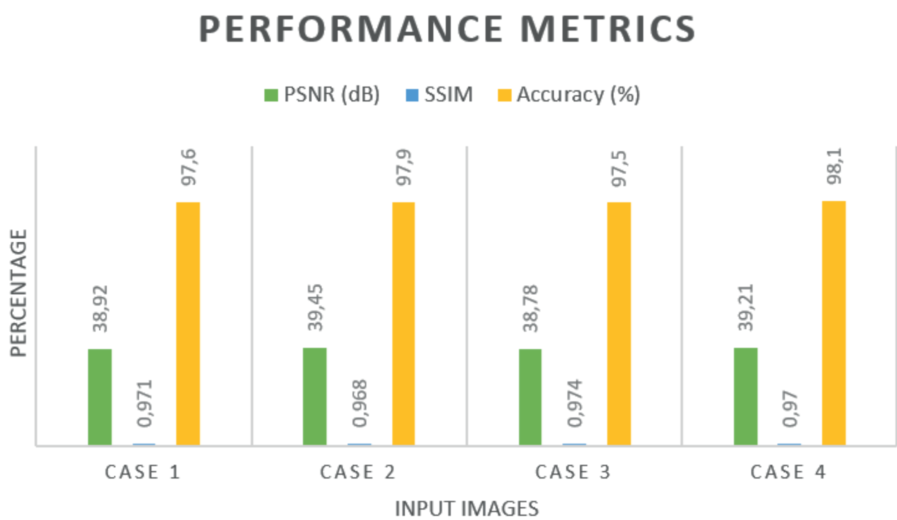

Figure 4.2. Graphical Representation of Proposed Metrics

Results suggest that during the fusion process, the most important attributes of the original image were preserved and the contrast was improved at the same time, with the ResNet50 based classifier yielding a mean accuracy of 97,8 %. Visual assessment confirmed that tumor margins were clearer in the fused images and diagnostic interpretation was improved as well. The new method was more of a challenge in terms of single-modality methods existing at present[7,8] in terms of structural fidelity and classification reliability. The combination of DWT-PCA fusion with deep learning not only reduced the amount of redundant information but also made the interpretation of the model more accessible for clinical use.[9,10,11,12] The fusion of traditional methods with deep neural networks has erected a framework wherein both interpretation and diagnostic precision have been improved.[13,14,15,16] Thus, the research confidently claims that multi-modal fusion along with AI-assisted classification could be the future of disease diagnosis and image-guided interventions.

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CONFLICT OF INTEREST

The authors assert that there are no conflicts of interest related to the research results presented.

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AUTHORSHIP CONTRIBUTION

Conceptualization: V Rajesh, B Rakesh Babu, Sk Hasane Ahammad, Mohammed R. Hayal, Ebrahim E. Elsayed.

Writing - original draft: V Rajesh, B Rakesh Babu, Sk Hasane Ahammad, Mohammed R. Hayal, Ebrahim E. Elsayed.

Writing - proofreading and editing: V Rajesh, B Rakesh Babu, Sk Hasane Ahammad, Mohammed R. Hayal, Ebrahim E. Elsayed.