

Image Fusion Using DWT for Bone Tumor Detection

¹Miss. Sonali B. Anantkar, ²Prof. S. R. Khot

E&Tc Department, DYPCOE, Kolhapur, India

Email: sonalianantkar23@gmail.com ²srkhot.dypcet@dypgroup.edu.in

Abstract: Bone tumors are complex conditions that require precise and reliable detection methods to improve diagnostic outcomes. This study presents an approach to bone tumor stage detection by integrating CT and MRI images using the Discrete Wavelet Transform (DWT) technique for image fusion. Despite attempts at automatic segmentation, manual segmentation was employed to accurately extract the tumor Region of Interest (ROI). Key features including standard deviation, variance, contrast, mean, homogeneity, entropy, energy, and radius correlation were computed from the segmented ROI. These features were classified using a Support Vector Machine (SVM) and compared against a pre-established database to determine the tumor stage. The methodology is implemented using MATLAB, demonstrating the potential for improved classification accuracy and laying the groundwork for advanced diagnostic tools in oncology.

Key Words: : Bone Tumor Detection, Image Fusion, Discrete Wavelet Transform (DWT), Support Vector Machine (SVM), Feature Extraction

1. INTRODUCTION

Bone tumors pose significant challenges in medical diagnostics due to their diverse nature and overlapping imaging characteristics with healthy tissue. Accurate detection and staging are crucial for effective treatment planning and patient prognosis. Traditional imaging modalities such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) provide complementary information about tumor structure and tissue composition. However, isolated use of these modalities may fail to capture the complete picture, necessitating the fusion of data from multiple sources. Image fusion techniques, particularly those based on the Discrete Wavelet Transform (DWT), have gained significant attention in medical imaging due to their ability to effectively combine spatial and spectral information. In this study, DWT is used to merge CT and MRI images, leveraging the complementary strengths of both modalities to achieve enhanced visualization and diagnostic clarity. While automatic segmentation methods are commonly used for their efficiency, in this case, manual segmentation was chosen to achieve higher accuracy and precise delineation of the tumor Region of Interest (ROI), ensuring reliable feature extraction for further analysis.

The segmented ROI is analysed to extract a set of texture and shape-based features, including standard deviation, variance, contrast, mean, homogeneity, entropy, energy, and radius correlation. These features serve as inputs to a Support Vector Machine (SVM), a robust classifier known for its efficacy in biomedical applications. By comparing these features against a database, the SVM enables accurate classification of tumor stages, providing critical insights for oncological diagnosis and treatment.

This paper outlines the methodology for image acquisition, fusion, segmentation, feature extraction, and classification. Experimental results, obtained through MATLAB implementation, validate the efficacy of the proposed approach, highlighting its potential to address the limitations of existing methods and contribute to the advancement of bone tumor diagnostics.

2. LITERATURE REVIEW:

The review in [1] explores the field of image fusion. Image fusion aims to integrate information from multiple sources to generate a single image with enhanced quality and reduced redundancy. The review compares different fusion methods, categorized into spatial and frequency domains, evaluating their effectiveness across various studies [2, 3]. It highlights the importance of image fusion in various applications, including scene description, feature extraction, and object recognition [4, 5]. Furthermore, the review delves into challenges and advancements in medical image fusion, specifically addressing brain tumor detection and characterization. Techniques involving NSCT, sparse representation,

and deep learning are discussed, along with the application of DWT and novel fusion rules for improved diagnostic accuracy [6, 7, 8, 9]. Finally, the review presents innovative approaches that combine wavelets to enhance spatial resolution and diagnostic quality in medical imaging, demonstrating their effectiveness in both simulated and real-world scenarios [10, 11].

A. Sharma et al. [12] propose a feature extraction-based machine learning model for bone cancer detection, achieving an impressive accuracy. This method uses GLCM, entropy, skewness, and HOG features, demonstrating high sensitivity toward cancerous regions, with plans for performance enhancement through advanced optimization techniques. E. Hossain et al. [13] explore tumor detection in bone MRI using a wavelet-based segmentation method combined with a KNN classifier, achieving a high classification accuracy with GLCM features, showcasing its potential for early diagnosis of bone cancer. S. Jana et al. [14] examine a pixel-based maximum selection rule combined with wavelet transformation for image fusion, which simplifies the process but suggests that more advanced fusion rules and filtering techniques could enhance the results. T. Balakrishna et al. [15] implement CT and MRI image fusion using the DWT technique in MATLAB 2021b, identifying the "max-max" method with Coif5 wavelet as the most effective, producing high-quality fused images for medical applications.

T. S. U. Suriya and P. Rangaraja [16] focus on tumor detection using DWT-based fusion for lung and brain images, showing the effectiveness of fusion rules like up-down and down-up fusion, evaluated with PSNR. K. Parmar et al. [17] combine wavelet transform with fusion rules for CT and MRI images, finding that the maximum fusion rule produces improved results with smaller RMSE and higher PSNR. R. V. Ravi et al. [18] explore the fusion of MRI and CT images using wavelet-based techniques, with the study demonstrating a significant improvement in tumor volume identification, offering 80% better identification compared to MRI or CT alone. Finally, M. P. Mirajkar and S. D. Ruikar [19] examine wavelet-based image fusion techniques, specifically focusing on the Stationary Wavelet Transform (SWT) at level 2, which outperformed other methods, as shown by performance evaluations using MSE, SNR, and PSNR. This body of work underscores the potential of wavelet-based fusion techniques in medical imaging, particularly for tumor detection and diagnosis, while also suggesting future improvements through advanced fusion rules and optimization techniques.

3. METHODOLOGY:

By using **MATLAB** to implement a robust system for bone tumor detection and classification. It begins with **dataset preparation**, where CT and MRI images are collected and augmented to create a larger dataset. The images are resized to a uniform resolution of **256 × 256 pixels**, ensuring consistency for subsequent processing steps.

Image fusion is carried out using the **Discrete Wavelet Transform (DWT)**, which combines the CT and MRI images to create an enhanced, detailed image by retaining significant features from both modalities. For segmentation, various automatic techniques, including intensity thresholding, Otsu's thresholding and K-means clustering, were tested but failed to deliver precise results due to noise and irregular tumor boundaries. Therefore, **manual segmentation** using MATLAB's *roipoly()* function is employed for accurate delineation of the tumor region.

The segmented tumor region is analysed to extract **statistical and texture features** such as contrast, entropy, anmean, which are stored in a **CSV database**. A **Support Vector Machine (SVM)** classifier then uses these features to predict the tumor stage by comparing them with the database. The MATLAB-based GUI visually displays the results, enabling efficient diagnostic interpretation.

4. MATLAB Implementation :

Tools and Techniques Used in MATAB :

The proposed method for bone tumor stage detection leverages MATLAB as the primary computational platform, chosen for its robust image processing capabilities and extensive library of functions tailored for medical imaging applications. Key techniques implemented include:

Image Fusion with Discrete Wavelet Transform (DWT):

To improve diagnostic quality, the fusion of CT and MRI images is performed using the Discrete Wavelet Transform (DWT) technique, specifically employing the Daubechies (db4) wavelet at three levels of decomposition. This multi-level wavelet decomposition extracts essential frequency-based features from both modalities. The DWT coefficients of the CT and MRI images are computed using MATLAB's *wavedec2()* function.

The fusion process follows a maximum selection rule, which selects the most informative coefficients from both the CT and MRI images, ensuring that the best features from each modality are retained in the final fused image. The fused image is then reconstructed by applying the inverse DWT using MATLAB's *waverec2()* function, combining the modified wavelet coefficients back into the image format.

The Discrete Wavelet Transform (DWT) of an image $f(x, y)$ can be represented as:

$$W(j, k) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(x, y) \varphi_{j,k}(x, y) dx dy$$

----- 1

Where,

- $W(j, k)$: The wavelet coefficient at scale j and translation k . These coefficients represent the transformed image in the wavelet domain.
- $f(x, y)$: The original image function in the spatial domain, where x and y are pixel coordinates.
- $\varphi_{j,k}(x, y)$: The wavelet basis function (or wavelet filter) at scale j and translation k . This function is used to decompose the image into different frequency components.
- $dx dy$: Represents the integral over the entire image domain, ensuring that the transformation accounts for all pixel values.

The inverse DWT reconstructs the fused image using:

$$f(x, y) = \sum_j \sum_k W(j, k) \varphi_{j,k}(x, y)$$

----- 2

This ensures that key spatial and frequency components from both images contribute to the final fused image.

Manual Tumor Segmentation:

Due to the limitations of automatic segmentation methods, manual segmentation is performed using the *roipoly()* in MATLAB to precisely extract the tumor Region of Interest (ROI).

Feature Extraction:

Texture and statistical features such as standard deviation, variance, contrast, mean, homogeneity, entropy, energy, and radius correlation are computed using built-in MATLAB functions and the Gray-Level Co-occurrence Matrix (GLCM).

Classification with SVM:

A pre-trained Support Vector Machine (SVM) model is employed for classifying the extracted features into specific tumor stages. The predict function in MATLAB facilitates this classification process.

The detailed steps for the implementation are as shown in below figure

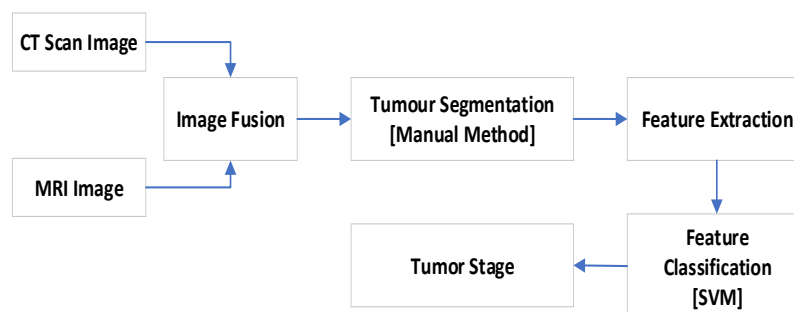


Fig.1. Block diagram of implemented work

The tumor stage detection method begins with image acquisition of CT and MRI images, which are fused using the Discrete Wavelet Transform (DWT) for enhancement. The fused image undergoes tumor segmentation to extract the Region of Interest (ROI), followed by feature extraction to compute statistical and texture features. These features are classified using an SVM model to predict the tumor stage, with results and visualizations displayed through a user-friendly GUI for diagnostic support.

5. EXPERIMENTAL RESULTS

The tumor segmentation is crucial step in the processing. Initially the automatic segmentation is tried on the test image. The segmentation results produced by these methods are illustrated in figure 2a to 2e including test image.

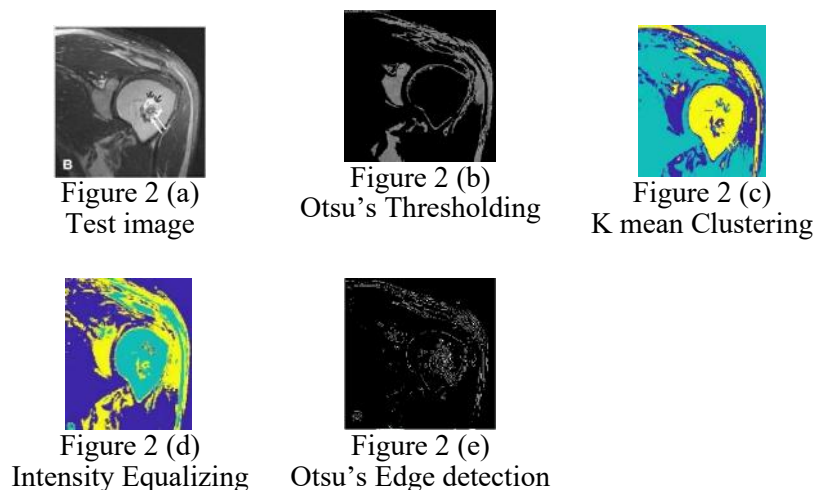


Figure 2(a) is the test image of bone tumor considered for the automatic segmentation of tumor region from the image. Figure 2(b) shows the result of use of Otsu's thresholding for automatic tumor segmentation. This method applies a global threshold to separate foreground and background based on pixel intensity. It can highlight structures but lacks precision in outlining tumor boundaries. Low contrast between tumor and surrounding tissue limits its effectiveness. Figure 2 (c) shows the result of K-means clustering for automatic segmentation, grouping pixels based on intensity or color similarity. While it separates regions, it lacks anatomical context, causing tumor boundaries to be unclear. Similar intensities between tumor and surrounding tissue lead to inaccurate segmentation. As shown in figure 2 (d) The image is enhanced using histogram equalization to improve contrast and visual clarity. This can make certain features more noticeable but does not achieve actual segmentation. It may also amplify noise or highlight irrelevant structures, affecting accuracy. Figure 2 (e) shows the result of combining Otsu's thresholding with edge detection (e.g., Canny or Sobel) to identify image boundaries. While it highlights edges, the results are often noisy and fragmented, lacking clear tumor enclosure. This limits its accuracy and effectiveness for precise tumor segmentation.

From the figures, it is evident that automatic segmentation methods fail to provide a perfectly segmented region. Therefore, a manual segmentation approach has been adopted to achieve more accurate results for tumor stage detection. The Graphical User Interface [GUI] provide a visual and interactive platform for the experimentation. The GUI designed to support the implemented work is as illustrated in fig 3

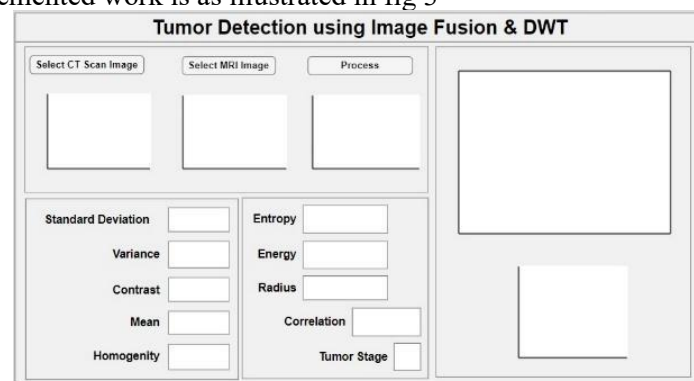


Fig 3 . Graphical User Interface [GUI] designed to achieve the tumor stage detection

The GUI consists of three main sections: an Image Input Section for uploading CT and MRI images and initiating processing, an Image Display Section for visualizing input, fused, and tumor-focused images, and a Statistical Feature Section for displaying tumor analysis metrics like contrast, entropy, and stage. This design streamlines tumor detection and feature analysis for medical imaging.

The successive stages in processing the bone tumor test image is as outlined below,

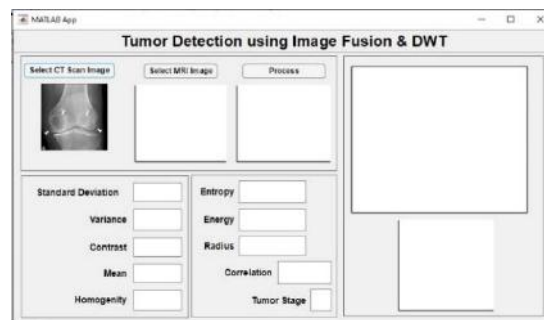


Figure 4 : Selecting the CT Scan Image

The user selects a CT scan image using the "Select CT Scan Image" button, which is displayed in the left placeholder. This image provides structural details of the bone region and forms the first input for processing.

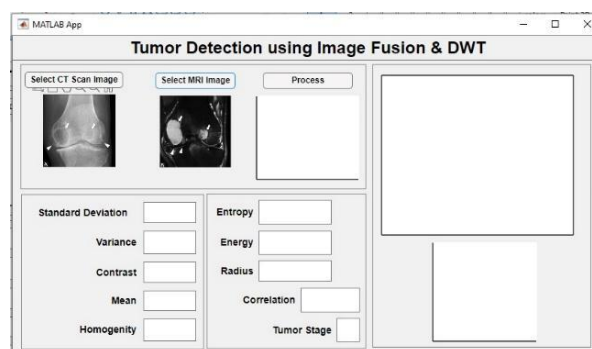


Figure 5 : Selecting the MRI Image

The user uploads an MRI image by clicking the "Select MRI Image" button. Displayed in the middle placeholder, this image captures soft-tissue details and complements the CT image for enhanced analysis.

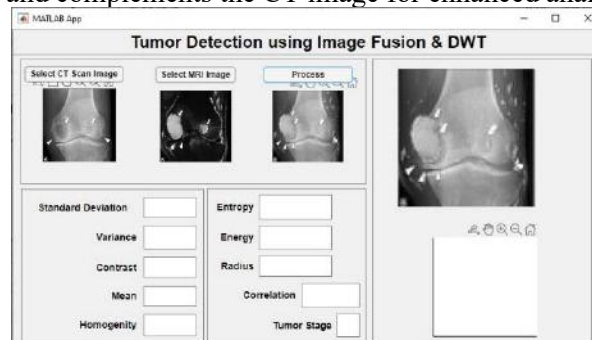


Figure 6 : Image Fusion and Processing

By clicking the "Process" button, the system fuses the CT and MRI images into a single, enhanced output. The fused image highlights the region of interest for tumor analysis.

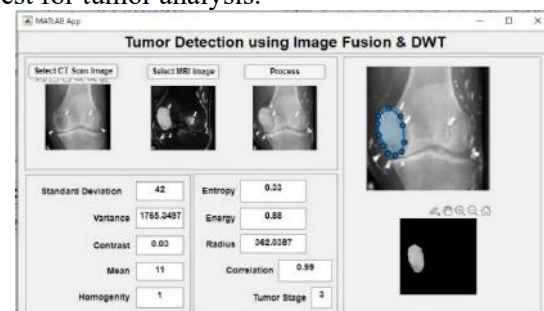


Figure 7: Tumor Detection and Feature Extraction

The system detects the tumor, outlines it in the fused image, and computes diagnostic metrics such as contrast, radius,

and tumor stage. These features help classify the tumor's severity. This step-by-step process integrates CT and MRI data, performs fusion, and extracts critical features for accurate bone tumor detection and staging.

6. CONCLUSION

This study presents an effective methodology for bone tumor stage detection by integrating CT and MRI images using Discrete Wavelet Transform (DWT)-based image fusion. The research highlights the limitations of automatic segmentation methods in achieving precise tumor delineation and demonstrates the superiority of manual segmentation in accurately extracting the Region of Interest (ROI).

The MATLAB implementation of the proposed approach underscores its potential to address diagnostic challenges by combining complementary imaging modalities, robust feature extraction, and machine learning-based classification. This methodology lays the groundwork for developing advanced diagnostic tools, contributing significantly to the precision and reliability of bone tumor detection and staging in clinical practice. Future enhancements could include automation of the segmentation process and integration with larger datasets to further refine the system's accuracy and scalability.

REFERENCES:

1. B. Pal, S. Mahajan, and S. Jain, "A Comparative Study of Traditional Image Fusion Techniques with a Novel Hybrid Method," in 2020 International Conference on Computational Performance Evaluation (ComPE), Shillong, India, 2-4 July 2020, doi: 10.1109/ComPE49325.2020.9200017.
2. Russell H. Al taie, Qayssar M. Jebur, "Image Fusion: A Review," Computer Reviews Journal, vol. 3, pp. 7-21, 2019. ISSN: 2581-6640.
- A. Salau, S. Jain, and E. J. Nnenna, "A review of various image fusion types and transforms," Indonesian Journal of Electrical Engineering and Computer Science, vol. 24, no. 3, pp. 1515-1522, Dec. 2021. DOI: 10.11591/ijeecs.v24.i3.pp1515-1522.
3. R. Johnson Suthakar, J. Monica Esther M.E., D. Annapoorani, and F. Richard Singh Samuel, "Study of Image Fusion - Techniques, Method and Applications," International Journal of Computer Science and Mobile Computing (IJCSMC), vol. 3, issue 11, pp. 469-476, November 2014. ISSN: 2320-088X.
4. U. Thakur, S. Rai, and Dr. S. K. Sahu, "A Study on Image Fusion for Pixel-Level and Feature-Based Techniques," Advances in Computational Sciences and Technology, vol. 10, no. 10, pp. 3047-3055, 2017. ISSN 0973-6107.
5. L. Chandrashekar and S. A., "A Hybrid Multimodal Medical Image Fusion Technique for CT and MRI Brain Images," Int. J. Comput. Vis. Image Process., vol. 8, no. 3, pp. 1-15, 2018. DOI: 10.4018/IJCVIP.2018070101.
6. S. Preethi and P. Aishwarya, "An efficient wavelet-based image fusion for brain tumor detection and segmentation over PET and MRI images," Multimedia Tools and Applications, 2021. Springer
7. C. Dwith and V. Angoth, "Wavelet Based Image Fusion for Detection of Brain Tumor," I.J. Image, Graphics and Signal Processing, vol. 1, pp. 25-31, Jan. 2013. DOI: 10.5815/ijigsp.2013.01.04.
8. V. Angoth, C. Dwith, and A. Singh, " , " Int. J. Comput. Vis. Signal Process., vol. 2, no. 1, pp. 1-7, 2013.
9. Y. Yang, D. S. Park, S. Huang, and N. Rao, "Medical Image Fusion via an Effective Wavelet-Based Approach," EURASIP Journal on Advances in Signal Processing, vol. 2010, Article ID 579341, pp. 1-13, 2010. doi: 10.1155/2010/579341.
- A. Krishn, V. Bhateja, H. Himanshi, and A. Sahu, "Medical image fusion using combination of PCA and wavelet analysis," in Proc. 2014 Int. Conf. Adv. Comput. Commun. Informatics (ICACCI), 24-27 Sept. 2014, doi: 10.1109/ICACCI.2014.6968636.
- A. Sharma, D. P. Yadav, H. Garg, M. Kumar, B. Sharma, and D. Koundal, "Bone Cancer Detection Using Feature Extraction Based Machine Learning Model," Computational and Mathematical Methods in Medicine , vol. 2021, Article ID 7433186, 13 pages, 2021. doi: 10.1155/2021/7433186.
10. E. Hossain, M. F. Hossain, and M. A. Rahaman, "An Approach for the Detection and Classification of Tumor Cells from Bone MRI Using Wavelet Transform and KNN Classifier," in Proc. International Conference on Innovation in Engineering and Technology (ICIET) , 27-29 Dec. 2018.
11. S. Jana, A. Pal, S. Ray, and P. Adhikary, "A Study on Wavelet Based Image Fusion," in Proc. 2nd International Conference on Electronics, Materials Engineering & Nano-Technology (IEMENTech) , 2018, doi: 10.1109/IEMENTECH.2018.
12. T. Balakrishna, Md A. Hannan, G. Nimishka, and G. V. Subba Reddy, "DWT-Based Image Fusion Technique in MATLAB: Identifying the Most Effective Method," in E3S Web of Conferences , vol. 391, Article 01076, 2023. doi: 10.1051/e3sconf/202339101076.

13. T. S. U. Suriya and P. Rangaraja, "Medical Image Fusion Using Discrete Wavelet Transform for Tumor Detection," Australian Journal of Basic and Applied Sciences , vol. 9, no. 16, pp. 104-109, Special Issue, 2015.
14. K. Parmar, R. Kher, and F. Thakkar, "Analysis of CT and MRI Image Fusion using Wavelet Transform," in Proc. 2012 International Conference on Communication Systems and Network Technologies (CSNT) , 2012, pp. 124-127. doi: 10.1109/CSNT.2012.36.
15. R. V. Ravi, S. M. V., S. K. M., T. A. Asharaf U., S. C. T., and S. Mohan M. T., "Performance Analysis of Wavelet Functions in Fusion of MRI and CT Images," in Proc. IEEE 7th International Conference on Smart Structures and Systems (ICSSS) , 2020. doi: 10.1109/ICSSS49878.2020.9395995.
16. M. P. Mirajkar and S. D. Ruikar, "Wavelet Based Image Fusion Techniques," in Proc. 2013 International Conference on Intelligent Systems and Signal Processing (ISSP) , 2013, pp. 77-81. doi: 10.1109/ISSP.2013.6860847.