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**Research Article**

# Multimodal Medical Image Fusion Techniques using CNN

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**ABSTRACT**

For the purpose of medical research, combining many medical images will improve the diagnosis of illness and highlight the intricate link between them. The technique of taking relevant visual information out of two or more photos and fusing them together to create a single fused image is called image fusion. From remote sensing to medical applications, image fusion is crucial in a wide range of image processing domains. Until recently, a variety of techniques have been employed for image fusion.

With the prevalence of health problems rising rapidly these days, it is imperative to comprehend human MRI and CT scan pictures in order to diagnose medical disorders accurately and promptly. Computed tomography (CT) and magnetic resonance imaging (MRI) are two common modalities in medical image processing that are used to extract information about hard and soft tissues, respectively. Nevertheless, it is extremely difficult to extract the necessary pathological traits to detect questionable tissue details using a single modality. Over the last few decades, a number of medical image fusion techniques have sought to overcome the previously described problem by combining complementing information from MRI and CT.

However, depending on variables like location, race, age, etc, the user's MRI and CT data fluctuation may cause variations in image fusion accuracy. The "Generalized Solution" that we propose in this work for the prompt diagnosis and early identification of health concerns using the merging of CT and MRI images which involves convolutional neural networks (CNNs) that can assist us in achieving a generic fusion strategy since they operate by extracting the key characteristics from CNNs without requiring particular data to be trained, may be used with a wide range of patients.

**Keywords:** *Image fusion, wavelet transform, SSI, CNN, Alex Net*

## I. INTRODUCTION

Image fusion is actually the method using which two or more images can be merged into a single image preserving the salient features from each of the original images. Image fusion is a technique used to integrate information from multiple images, often acquired from different sources or modalities, to create a single more informative image [1]. This process aims to enhance the overall quality, clarity, and interpretability of the resulting image by combining complementary information from the input images [2]. some common scenarios where image fusion is required like multimodal medical imaging, remote sensing, surveillance and security, computer vision & robotics, and many more [1]. For example, in multimodal

medical imaging, different imaging modalities, such as magnetic resonance Imaging (MRI), computed tomography (CT) provides distinct information about the same anatomical structure [9].

Image fusion helps in creating a comprehensive image that combines the strength of each modality [2][3][5][9]. Traditionally computer vision image fusion techniques can be categorised into spatial domain methods, frequency domain methods and transform domain methods [6]. The choice of method depends upon the characteristics of the image being fused and the specific requirements of the application [4][26].

## II. RELATED WORK

Many image fusion techniques have been proposed in the last few years, including Brovey Transform (BT), Principal component analysis (PCA), wavelets, and Intensity hue-saturation (ISH). Brovey Transform technique used to combine multispectral (MS) panchromatic images (PAN). This technique aims to enhance the spatial resolution of the multispectral data by incorporating high-resolution information from the panchromatic image [1].

The Brovey transform is particularly common in remote sensing applications with the advantage of being computationally efficient and easy to implement [1]. However, it assumes a linear relationship between the multispectral and panchromatic images, which may not always be the case [1]. In some situations, more advanced fusion methods that consider non-linear relationships or other statistical properties may be preferred [1].

The Intensity-Hue-Saturation transform is a color space transformation commonly used in medical image processing, computer vision, and remote sensing applications. It separates an image into three components: Intensity (I), Hue (H), and saturation (S) [11]. IHS transformation is particularly useful in image fusion, where information from different sensors or sources is combined to create a composite image [11]. In image fusion, the IHS transform is often applied to high-resolution panchromatic (grayscale) images and lower-resolution multispectral (color) images [10]. The key advantage of IHS is that it preserves the spectral information from the multispectral image while enhancing the spatial details from the panchromatic image [10]. It helps to incorporate this high-resolution spatial information into the color images [10]. IHS comes with certain disadvantages like color distortion, loss of spectral information, Incompatibility with all scenes, and sensitivity to image misregistration so it has limited enhancements in certain applications [10].

Principal Component Analysis (PCA) fusion is another technique used for combining information from different image sources, often applied in remote sensing and image processing [12]. PCA is a mathematical technique that transforms the original correlated data into a new set of uncorrelated variables called principal components [12]. In image fusion, PCA is used to extract essential information from multispectral and panchromatic images [12]. It reduces the dimensionality of the multispectral data, which can lead to reduced storage and computational requirements [12]. PCA optimally represents the data in terms of variance. Some of the challenges & considerations with PCA fusion are sensitivity to noise and potential for color distortion [12]. The effectiveness of PCA fusion depends on the characteristics of the input data and the goals of the application. Hence it may not be universally optimal for all scenarios [12].

Wavelet image fusion is a technique used for combining information from images with the goal of creating a fused image that retains the relevant features of each input image [20]. This technique is particularly useful for combining images with different spatial or spectral characteristics Wavelet transforms divide an image into different scales and orientations, capturing both high-frequency details and low-frequency approximations [13]. Common wavelet transforms include the discrete wavelet transform (DWT) and the continuous wavelet transform (CWT) [20]. The wavelet coefficients from corresponding scales and orientations of different input images are combined or fused to create a new set of coefficients for the fused image [20]. Different fusion rules can be applied, such as selecting the maximum or average value at each position [20]. The fused wavelet coefficients are then transformed back into the spatial domain using the inverse wavelet transform, resulting in the final fused image [20]. Wavelet fusion is adaptable to different types of images and can handle images with varying spatial resolutions [13]. It helps to reduce blocked artifacts that may be present in some other fusion techniques, particularly when dealing with compressed images [14]. Wavelet image fusion is widely used in various applications including remote sensing, medical imaging, and computer vision [13].

## III. PROPOSED METHODOLOGY

The proposed methodology proposes the image using convolutional neural networks (CNNs) in the medical field [37]. The purpose of this research is not just to explore new horizons in medical imaging but to tackle head-on the disadvantages and limitations that have challenged the existing methods in image fusion [9]. Convolutional Neural Networks can help us achieve a generalized fusion technique, as the CNN is not trained on any specific data [6] and works by extracting the major features from CNN. This paper extensively studies different convolutional networks to perform multimodal image fusion [25][26]. To the best of our knowledge, our research represents a unique contribution as it is the first to empirically investigate fusion using different CNNs concurrently using the same dataset [37]. This distinctive approach sets our work apart from existing studies in the field, as we strive to comprehensively explore and compare the effectiveness of these fusion strategies in a unified and rigorous manner [27]. By conducting a simultaneous examination, we aim to provide a more robust and nuanced understanding of the advantages and limitations of each fusion technique, offering valuable insights for future research and practical applications [9].

**Algorithm 1: Image Registration and Fusion**

**input:** CT and MRI image of the patient captured from the same angle.

**output:** An image that retains information from both CT and MRI image.

Select one image as a base to align other images uniformly.

**foreach** image in multimodal images

  correct image scaling, rotation, and position according to the reference image.

  pass the image through a Wavelet Filter. The Wavelet Filter outputs 4 images given a single input image.

**end**

**foreach** output image from the Wavelet Filter for all images in multimodal images**.**

  Pass the images through A Pretrained Neural Network (VGG19, AlexNet, etc.)

  Extract the output from one of hidden layer of the Neural Network.

  Save the Fused output from the hidden layer.

**end**

Apply Inverse Wavelet Filter on the fused output from hidden layers. The Inverse Wavelet Filter takes 4 input images and outputs a single output image.

### *A. Image Registration:*

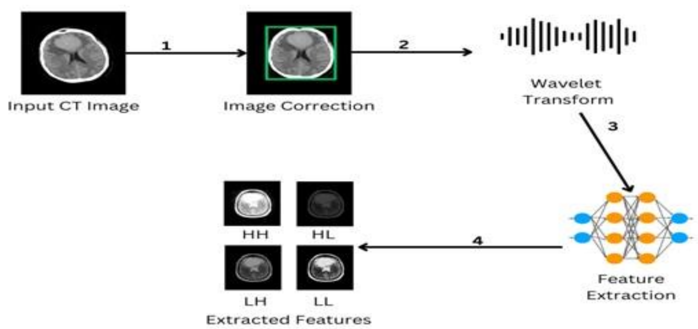


*Fig 1: Feature Extraction and Fusion Architecture on Medical CT Image*

Figure 1 shows the architecture complete of the Feature Extraction and Fusion process. The registration of CT and MRI images is done using a Procrustes algorithm [8]. The Procrustes algorithm defines a linear transformation of the points for an image so that it aligns with the other image.

Similarly, Figure 2 shows the feature extraction architecture for MRI Image from the input image to the extracted features.

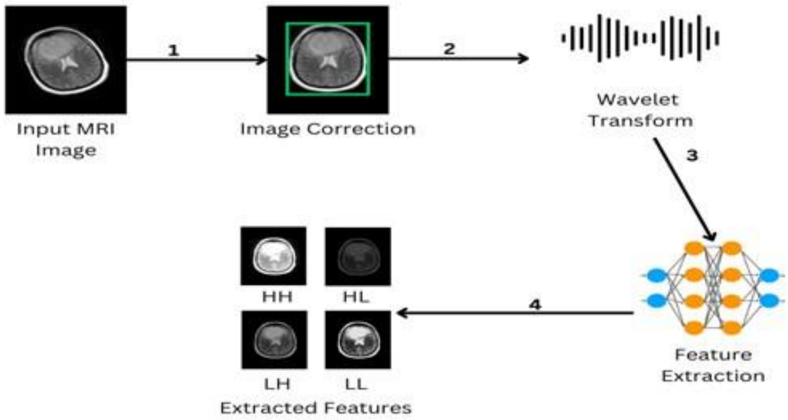


*Fig 2: Feature Extraction and Fusion Architecture on Medical MRI Image*

The Procrustes algorithm ensures that the image is centred around the mean and is normalized [8].

$$X_0 = X - \mu X$$

$$Y_0 = Y - \mu Y$$

The rotation and scaling transformation is done using Singular Value Decomposition (SVD)[8]. SVD Decomposes the cross-

covariance matrix of the centered and normalized image into three factors U, S, $V^T$ where, U and $V^T$ are the rotation factors

for the image, whereas S is the scaling factor. The SVD formula is as follows:

$$A = U.S.V^T$$

For scaling transformation, a scaling factor is calculated using the S matrix containing non-directional singular values of S and the A is the product of the transposition of the centered image and target image. The length of both the images $normX$ and $normY$[8].

$$A = X_0^T * Y_0$$

$$b = trace(S\ .\ A)\ .\ \frac{normX}{normY}$$

The translation vector $c$ represents the difference between the centroids of the centered image and the target image to ensure the positioning of both images is correct. The previously calculated scaling factor $b$ and T are obtained by multiplication of left singular vector U and transpose of right singular vector V extracted from the SVD operation.

$$T = V\ .\ U^T$$

$$c = \mu_X - b\ .\ (\mu_Y\ .T\ )$$

The transformed image Y is computed by applying the rotation T and scaling b and translation c to the original Y. The amount of alignment is measured by the normalized residual sum of squared errors between X and the aligned Y [8].

### *B. Image Fusion:*

The individual aligned images are passed through a wavelet transform [15]. The haar coefficient is used to transform the images into frequencies. As shown in Figure 3, one single CT image is divided into 4 filters namely Low High sub band (LH), High Low sub band (HL), Low Low sub band (LL), and High High sub band (HH) by applying the haar coefficient first on the image and then again on the High band and Low band filters generated from the original image. The same process is repeated for the aligned MRI image as well [15].

The detailed and approximate sub band image pairs where each pair consists of a sub band (for example, a Low High sub band CT image is paired with a Low High sub band MRI image) are fed into a Convolutional Neural Network (CNN)[15].

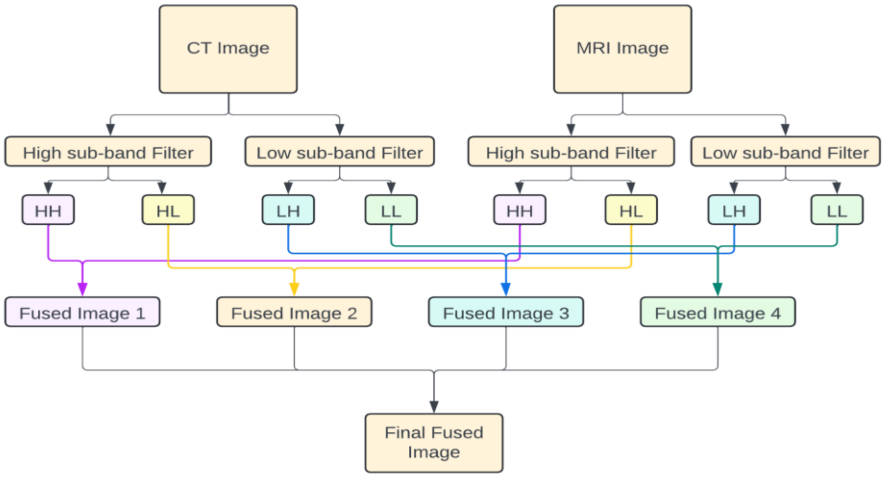


*Fig 3: Wavelet transform filters for image fusion*

The input sub-band images are only forwarded through the Convolutional Neural Network (CNN) for a couple of hidden layers [37]. Feeding an image through the first few hidden layers of a CNN reveals how it learns hierarchical representations, transitioning from low-level edges and textures to higher-level semantic concepts. The first convolution layers detect simple edges and gradients. Deeper layers combine these into motifs and patterns [37].

The proposed image fusion algorithm was tested with popular Neural Network architectures like VGG19 and Alex-Net [28]. Multiple samples of hidden layers were tested using layers 2-4 proved to be the most accurate [28].

### *C. Fusing the Sub band Images into a Single Image:*

After the Convolution Operation is done on Sub band images, a Summation operation is done to fuse all the sub band images

into a single image [28]. Each Feature map is calculated by passing the input tensor through CNN, the sum of feature maps is concatenated into a single feature vector.

$$features = Concatenate(sum(feature\ map_1), \quad sum(feature\ map_2), \dots, \quad sum(feature\ map_n)\ )$$

For each Feature Vector weights are calculated using the softmax activation function and a final fused image is formed by multiplying the image with the corresponding weights.

$$weights = Softmax\big(Interpolate(features)\big)$$

$$fused\ image\ = \sum_{i=1}^{n} \quad (img_i * weights_{:,i})$$

The summation of feature maps is concatenated and passed through a softmax function to obtain a set of weights that represent the relative importance or contribution of each input image to the fused output image. These weights are used to compute a weighted sum of the input image, and the element-wise maximum of this weighted sum across different feature map levels is returned as the fused output image.

### *D. Image Reconstruction using Inverse Wavelet Transform:*

After the images from both the CT (Computed Tomography) and MRI (Magnetic Resonance Imaging) scans have been decomposed using a wavelet transform [42], They are represented as coefficients in different frequency sub bands. Each sub band captures specific frequency information and spatial details of the original images [28]. The decomposed sub band images from both the CT and MRI scans are then passed through an inverse wavelet transform. The inverse wavelet transform reconstructs the original images from their wavelet coefficients [43], essentially reversing the decomposition process. The fused sub band images are passed through the inverse wavelet transform in the same sequence as they were decomposed. This sequence typically follows the pattern LL, (LH, HL, HH) [20].

LL represents the low-frequency, low-resolution approximation component of the image. This component captures the overall structure and large-scale features [42]. LH, HL, and HH represent the high-frequency detail components of the image. Each of these components captures different types of details or textures in different directions [20]. The output of the inverse wavelet transform [43] is a single image that combines the fused features of both the CT and MRI scans. By reconstructing the images in the LL, LH, HL, and HH sequence, the resulting image preserves the overall structure and large-scale features while incorporating the high-frequency details from both scans. Overall, this process allows for the fusion of complementary information from CT and MRI scans, resulting in a single composite image that potentially provides more comprehensive diagnostic information than either modality alone. This fused image can aid medical professionals in making more accurate diagnoses or assessments of various medical conditions.

## IV. RESULTS AND DISCUSSION

The image fusion technique was tested with multiple Convolutional Neural Networks with a variety of hidden layer cut-off ranges [28]. Figure 3 shows the fusion process performed on the same CT and MRI sample with different Neural Networks. AlexNet [7] favours retaining most features of either of the two modalities, whereas VGG19 retains information from both the CT and MRI images fairly well. The edge detection is also more refined and accurate in the VGG19 Fused images as compared to its counterpart [28].

The Structural Similarity Index or SSI was used as a metric to determine the number of features retained from the original CT and MRI images [36]. Two samples were tested out of which the first sample had a brighter MRI image than the MRI image and the second sample had a brighter CT image than the MRI image. This was done to ensure that information is retained from both images regardless if one of the images has a higher brightness.

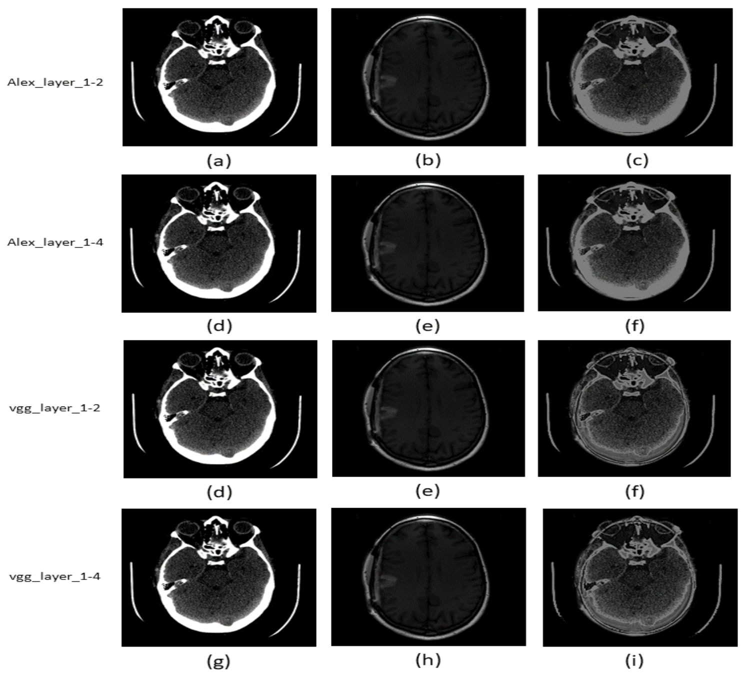


*Fig.3: Image fusion using multiple CNN with a variety of hidden layer cut-off range*

Table 1: Structural Similarity Index of Fusion Images compared to MRI and CT images.

| CNN and Layer | SSI of Fusion and MRI (sample1) | SSI of Fusion and CT (sample1) | SSI of Fusion and MRI (sample2) | SSI of Fusion and CT (sample2) |
|---|---|---|---|---|
| AlexNet Layer 1-2 | 0.535 | 0.383 | 0.318 | 0.711 |
| AlexNet Layer 1-4 | 0.536 | 0.385 | 0.319 | 0.715 |
| VGG19 Layer 1-2 | 0.549 | 0.328 | 0.319 | 0.691 |
| VGG19 Layer 1-4 | 0.617 | 0.33 | 0.318 | 0.687 |

Table 1 demonstrates the results of two different samples that are fused using Alexnet and VGG19 networks. It shows the structural similarity index (SSI) values between different combinations of image fusion techniques and medical imaging modalities for two samples, across different layers of convolutional neural networks hence compares the different CNN networks with their Structural Similarity Index score.

CNN and layer indicate the specific CNN architecture and the layers within that architecture used for feature extraction. In this table, two popular architectures, AlexNet and VGG19, are mentioned. SSI of fusion and MRI (Sample1 and Sample 2) represents the SSI between the fused image and MRI image for sample 1 and Sample 2. SSI is a metric used to measure the similarity between two images. Higher values indicate greater similarity. SSI of fusion and CT (sample 1 and Sample 2) represents the SSI between the fused images and CT image for sample 1 as well as Sample 2. It is used to identify the similarity between the Fused image and the original MRI or CT image. For AlexNet Layer 1-2, the SSI value for fusion with MRI in sample 1 and sample 2 are 0.535 and 0.318 respectively. Similarly, the SSI values for fusion with CT in sample 1 and sample 2 are 0.383 and 0.711 respectively. For VGG19, the SSI values for fusion with MRI in sample 1 and sample 2 are 0.617 and 0.318 respectively. Similarly, the SSI values for fusion with CT in sample 1 and sample 2 are 0.33 and 0.687 respectively. These values indicate how well the fused images, obtained through different fusion techniques, match with original MRI and CT images. Higher the SSI values suggest better fusion quality, indicating that the fused image is more similar to the original medical image. The variations across different CNN architectures and layers highlight the impact of feature extraction on the fusion process. As we can see, the overall performance of VGG19 is better as it tries to retain more information from both the MRI and CT images as compared to AlexNet which heavily favours either the CT image or the MRI image depending upon which image has the higher intensity.

## V. CONCLUSION AND FUTURE SCOPE

In summary, the utilization of Convolutional neural networks (CNNs) for fusing multimodal images emerges as a highly effective approach capable of accommodating a diverse range of image types[28]. As shown in the above results, using VGG19 with a cutoff of 1-4 Layers is very effective for Fusing CT and MRI images together without the loss of significant features from the images. This method not only streamlines the fusion process but also obviates the necessity for extensive modal training, leveraging the advantageous pre-trained models that excel in retaining the structural integrity of images[28]. Notably, comparative studies, as outlined in the literature, consistently demonstrate the superiority of the VGG19 model over traditional spatial fusion techniques, particularly in preserving critical features such as edges [28].

Beyond its immediate benefits in image fusion, this technique yields broader implications, particularly in medical imaging applications [9]. By generating fused images of superior quality and detail, these neural network-driven approaches provide an invaluable foundation for subsequent tasks, such as image segmentation [9]. For instance, in the context of brain MRI and CT scans, the fused images serve as an optional substrate for enhancing the precision of tumour detection and delineation [9]. By leveraging the rich information encapsulated within these fused representations, image segmentation algorithms can more accurately identify and characterize pathological anomalies, ultimately facilitating more effective clinical diagnoses and treatment planning. In essence, the adoption of CNN-based fusion methodologies not only revolutionizes the process of integrating multimodal images but also catalyses advancements in downstream tasks, particularly in critical domains like medical imaging, where precision and accuracy are paramount. Furthermore, the Fused images can be used as a base for Image Segmentation to improve tumour detection in brain MRI and CT images.

## REFERENCES


[1] Reham Gharbia, Ahmad Taher Azar, Ali El Baz, Aboul Ella Hassanien,"Image Fusion Techniques in Remote Sensing", arXiv: 1403.5473, vol 1, Mar 2014, https://doi.org/10.48550/arXiv.1403.5473

[2] Nivedita Jha, Aumreesh Ku. Saxena,Amit Shrivastava,Manish Manoria,"A Review on Various Image Fusion Algorithms", Proceeding International conference on Recent Innovations is Signal Processing and Embedded Systems (RISE-2017) 27-29 October,2017

[3] Mamta Sharma ,"A Review : Image Fusion Techniques and Applications",IJCSIT, International Journal of Computer Science and Information Technologies, Vol. 7 (3), 2016, 1082-1085.

[4] Deepak Kumar Sahu, M.P.Parsai,"Different Image Fusion Techniques –A Critical Review", International Journal of Modern Engineering Research (IJMER), Vol. 2, Issue. 5, Sep.-Oct. 2012 pp-4298-4301, ISSN: 2249-6645

[5] Harpreet Kaur,Deepika Koundal, Virender Kadyan, "Image Fusion Techniques: A Survey", Archives of Computational Methods in Engineering, Vol. 28, 2021,https://doi.org/10.1007/s11831-021-09540-7

[6] Zhe Guo, Xiang Li, Heng Huang, Ning Guo, Quanzheng Li, "MEDICAL IMAGE SEGMENTATION BASED ON MULTI-MODALCONVOLUTIONAL NEURAL NETWORK: STUDY ON IMAGE FUSION SCHEMES", IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018), April 4-7, 2018, Washington, D.C., USA

[7] K.Kavitha, B. Thirumala Rao, B. Sandhya ,"Evaluation of Distance Measures for Feature based Image Registration using AlexNet", (IJACSA) International Journal of Advanced Computer Science and Applications,Vol. 9, No. 10, 2018.

[8] Kilian M. Pohl, John Fisher, James J. Levitt, Martha E. Shenton, Ron Kikinis,W. Eric L. Grimson, and William M. Wells, "A Unifying Approach to Registration, Segmentation and Intensity Correction", , MICCAI (Springer-Verlag Berlin Heidelberg)2005, LNCS 3749, pp. 310–318, 2005

[9] Rajalingam Balakrishnan, Rainy Priya,"Multimodal Medical Image Fusion based on Deep Learning Neural Network for Clinical Treatment Analysis", International Journal of ChemTech Research, Vol.11 No.06, ISSN: 0974-4290, May 2018, DOI: 10.20902/ijctr.2018.110621

[10] X. Xue, A Wang, H. Wang and F. Xiang, "A fusion method of multi-spectral image and pan image based on NSCT and IHS transform", Intelligent Control and Information Processing (ICICIP), 2012 Third International Conference, 2012, Pp. 640 – 643.

[11] D. Grasso, "Applications of the IHS color transformation for 1:24,000-scale geologic mapping: A low cost SPOT alternative Photogrammetric Engineering & Remote Sensing", 1993,. Vol. 59, No. 1, Pp. 73-80.

[12] S. Kumar and S. Muttan, "PCA Based Image Fusion. The Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery XII", Orlando (Kissimmee), FL, USA, 2006.

[13] C. YUNHAO, D. LEI, L. JING, L. XIAOBING and S. PEIJUNA, "New wavelet-based image fusion method for remotely sensed data", International Journal of Remote Sensing, 2006, Vol. 27, No. 7, 10 April 2006, 1465–1476.

[14] Paul Hill, Mohammed E. Al-Mualla and David Bull, "Perceptual Image Fusion using Wavelets", IEEE TRANSACTIONS ON IMAGE PROCESSING, DOI 10.1109/TIP.2016.2633863.

[15] Deepika.L, Mary Sindhuja.N.M "Performance Analysis of Image Fusion Algorithms using HAAR Wavelet", International Journal of Computer Science and Mobile Computing, Vol.3 Issue.1, January- 2014.

[16] Yi Ding , Wei Zheng, Ji Geng, Zhen Qin ,Kim-Kwang Raymond Choo, Zhiguang Qin and Xiaolin Hou ,"MVFusFra: A Multi-View Dynamic Fusion Framework for Multimodal Brain Tumor Segmentation", IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS, VOL. 26, NO. 4, APRIL 2022.

[17] Saqib Ali , Jianqiang Li, Yan Pei, Khalil Ur Rehman, "A Comprehensive Survey on Brain Tumor Diagnosis Using Deep Learning and Emerging Hybrid Techniques with Multi-modal MR Image", Archives of Computational Methods in Engineering, DOI:10.1007/s11831-022-09758-z

[18] Siraj Khan , Majid Harouni , Rashid Abbasi , Sajid Iqbal, "Brain tumor segmentation using K-means clustering and deep learning with synthetic data augmentation for classification", Microscopy Research and Technique, February 2021, https://www.researchgate.net/publication/346440471.

[19] Yun Jiang, Yuan Zhang , Xin Lin , Jinkun Dong, Tongtong Cheng and Jing Liang, "SwinBTS: A Method for 3D Multimodal Brain Tumor Segmentation Using Swin Transformer", Transformer. Brain Sci. 2022, 12, 797,https://doi.org/10.3390/brainsci12060797.

[20] P.R. Hill, C.N. Canagarajah and D.R. Bull, “Image Fusion Using Complex Wavelets.” Proceeding of the 13th British Machine Vision Conference, pp. 487–496, 2002.

[21] V. Petrovic and C. Xydeas, “Gradient based multiresolution image fusion,” IEEE Transactions on Image Processing, vol. 4, no. 2, pp. 163–183, 2004.

[22] J.J. Lewis, R.J. O’Callaghan, S.G. Nikolov, D.R. Bull and C.N. Cana- garajah, “Pixel and region-based image fusion with complex wavelets,” Information Fusion, vol. 8, no. 2, pp. 119–130, 2007.

[23] S. Li, J. T. Kwok, and Y. Wang, “Multifocus image fusion using artificial neural networks,” Pattern Recognition Letters, vol. 23, no. 8, pp. 985 –997, 2002.

[24] H. Chen and P. K. Varshney, “A human perception inspired quality metricfor image fusion based on regional information,” Information fusion,vol. 8, no. 2, pp. 193–207, 2007.

[25] B.Rajalingam, Dr. R.Priya, “Multimodality Medical Image Fusion Based on Hybrid Fusion Techniques” International Journal of Engineering and Manufacturing Science. Volume 7, No. 1, 2017,pp. 22-29

[26] B.Rajalingam, Dr. R.Priya, “A Novel approach for Multimodal Medical Image Fusion using Hybrid Fusion Algorithms for Disease Analysis” International Journal of Pure and Applied Mathematics, Volume 117, No. 15, 2017, pp. 599-619

[27] B.Rajalingam, Dr. R.Priya, “Hybrid Multimodality Medical Image Fusion Technique for Feature Enhancement in Medical Diagnosis” International Journal of Engineering Science Invention (IJESI), Volume 2, Special issue, 2018, pp. 52-60

[28] Yu Liu, Xun Chen, Juan Cheng, Hu Peng, “A Medical Image Fusion Method Based on Convolutional Neural Networks”20th International Conference on Information Fusion, Xi'an, China - July 10-13, 2017

[29] S. Chavan, A. Pawar and S. Talbar “Multimodality Medical Image Fusion using Rotated Wavelet Transform” Advances in Intelligent Systems Research, Vol. 137, 2017, pp. 627-635

[30] UdhayaSuriya TS, Rangarajan P “Brain tumour detection using discrete wavelet transform based medical image fusion” Biomedical Research, 28 (2), 2017, pp. 684-688

[31] B. H. Menze et al., "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)," IEEE Transactions on Medical Imaging, vol. 34, no. 10, pp. 1993-2024, 2015.

[32] H. Cai, R. Verma, Y. Ou, S. k. Lee, E. R. Melhem, and C. Davatzikos, "Probalistic Segmentation of Brain Tumors based on Multi-Modality Magnetic Resonance Images" in 2007 4th IEEE International Symposium on Biomedical Imaging: From Nano to Macro, pp. 600-603, 2007.

[33] S. Klein, U. A. van der Heide, I. M. Lips, M. van Vulpen, M. Staring, and J. P. W. Pluim, "Automatic segmentation of the prostate in 3D MR images by atlas matching using localized mutual information," Medical Physics, vol. 35, no. 4, pp. 1407-1417, 2008.

[34] Y. Yang, "Multimodal Medical Image Fusion through a New DWT Based Technique," in 2010 4th International Conference on Bioinformatics and Biomedical Engineering, 2010, pp. 1-4.

[35] R. Singh and A. Khare, "Fusion of multimodal medical images using Daubechies complex wavelet transform – A multiresolution approach," Information Fusion, vol. 19, no.Supplement C, pp. 49-60, 2014.

[36] A. P. James and B. V. Dasarathy, "Medical image fusion: A survey of the state of the art," Information Fusion, vol. 19, no. Supplement C, pp. 4-19, 2014.

[37] Li, X et al. .Self-paced Convolutional Neural Network for Computer Aided Detection in Medical Imaging Analysis, Machine Learning in Medical Imaging: 8th International Workshop, MLMI 2017, pp. 212-219.

[38] Wu, D et al, "End-to-End Abnormality Detection in Medical”, arXiv:1711.02074, 2017.

[39] Liu Wei,"An image coding method based on multi wavelet transform",4th International Conference on Image and Signal Processing ,voL2,2011.

[40] Lijun Liu; Hui Zhang ,"Application on Image Fusion Based on Balanced Multi-Wavelet ", International symposium on Intelligence Information Processing and Trusted Computing (IPTC),2010.

[41] Sekhar, Prasad, M.N.G, "A novel approach of image fusion on MR and CT images using wavelet transforms ",International Conference on Electronics Computer Technology, vol.4,2011.

[42] R.J.Sapkal, S.M.Kulkarni “Image Fusion based on Wavelet Transform for Medical Application” International Journal of Engineering Research and Applications ISSN: 2248-9622 Vol. 2, Issue 5, September- October 2012.

[43] Kiran Parmar, Rahul K Kher, Falgun N Thakkar “Analysis of CT and MRI Image Fusion using Wavelet Transform”, International Conference on Communication Systems and Network Technologies 2012.

[44] Dhakan, Parth, Amit Mandaliya, Akshat Limbachiya, and Harsh Namdev Bhor. "Brain stroke detection using machine learning." In AIP Conference Proceedings, vol. 3227, no. 1. AIP Publishing, 2025.

[45] J. V. . Terdale, V. . Bhole, H. N. . Bhor, N. . Parati, N. . Zade, and S. P. . Pande, “Machine Learning Algorithm for Early Detection and Analysis of Brain Tumors Using MRI Images”, IJRITCC, vol. 11, no. 5s, pp. 403–415, Jun. 2023

[46] Bhor, H.N., Kalla, M. (2021). A Survey on DBN for Intrusion Detection in IoT. In: Zhang, YD., Senjyu, T., SO–IN, C., Joshi, A. (eds) Smart Trends in Computing and Communications: Proceedings of SmartCom 2020. Smart Innovation, Systems and Technologies, vol 182. Springer, Singapore. https://doi.org/10.1007/978-981-15-5224-3_33.

[47] H. N. Bhor and M. Kalla, "An Intrusion Detection in Internet of Things: A Systematic Study," 2020 International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2020, pp. 939-944, doi: 10.1109/ICOSEC49089.2020.9215365.

[48] Bhole, V. ., Bhor, H. N. ., Terdale, J. V. ., Pinjarkar, V. ., Malvankar, R. ., & Zade, N. . (2023). Machine Learning Approach for Intelligent and Sustainable Smart Healthcare in Cloud-Centric IoT. International Journal of Intelligent Systems and Applications in Engineering, 11(10s), 36–48.