Classification of Multimodal Brain Images employing a novel Ridgempirical Transform

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Abstract

With the evolution of technology, the assistance of hi-tech computers in the medical field occasionally involves image fusion methods. Detection and diagnosis of a disease with a single image can be tedious and difficult for doctors but with the adaptation of medical image fusion, a path for additional improvements can be paved. In this paper, the authors have proposed a Ridgempirical transform where filter banks are fused, & classified using machine learning Technique. The objective of this research is to implement different pre-processing techniques on CT-MR images of the same patient. The filter banks and spectrum are evaluated using Ridgelet Empirical Wavelet Transform (EWT) which was fused. The images are classified using Support Vector Machine. 89.5% and 86.5% of accuracy are obtained using top-hat and morphological transforms respectively. Authors have also tried other pre-processing techniques but the results employing top hat transform outperform the other techniques. To validate the proposed algorithm, the authors have used a fused CT-MR image which was pre-processed using the top-hat transform technique, and 92.1% accuracy is observed.

KeyWords: Imaging modalities, Medical image fusion, Pre-processing, Empirical Wavelet Transform, Top-hat transforms.

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Introduction

Image Processing is a technique that plays different procedures on an image. The continuum from picture handling to PC vision can be separated into low-, mid-and significant level processes [1]. One of the main uses of image processing is image fusion. Image Fusion has been used in numerous applications. The fusion type in picture handling is multi-temporal, which perceives two unique points [2]. Different methods of picture combination can be delegated at three levels namely (a) pixel level, (b) decision level, and (c) feature level [3]. Pixel level procedures for picture combination straightforwardly incorporate the Information from input pictures for additional PC handling errands [4]. Features level strategies for image fusion involve the extractions of relevant features like pixel intensities, surfaces, or edges making strengthening blended highlights [5, 6]. Multi-view combination of images from a similar methodology and taken simultaneously however from various perspectives. Multi-temporal fusion of pictures taken at various times to identify changes between them or to orchestrate reasonable pictures of articles that were not captured in an ideal time. Multi-focus fusion of pictures of a 3D scene taken over and again with different central lengths. Multimodal combination of images coming from various sensors [7, 8].

Brain anomalies are categorized depending on the position and form of tissues, which aids in the diagnosis of cancerous or non-cancerous abnormalities [9]. Infections, bleeding, hemorrhage, epilepsy, and cancers are a few examples of brain defects. Anatomical imageries like Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Single Photon Emission Computed Tomography (SPECT), and Positron Emission Tomography (PET) can aid with this [10].

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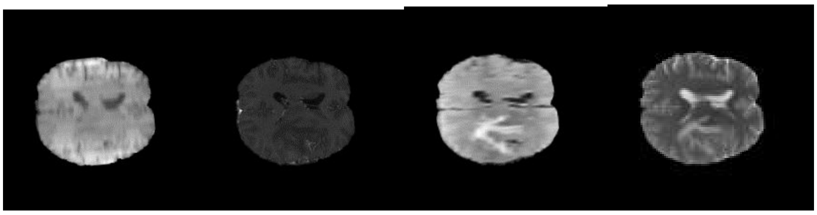
MRI and CT are among the most widely used radiology modalities for detecting neurodegenerative problems and diagnosing hemorrhage, acute stroke, and inflammation, with the assistance of image data processing [11]. The CT scans enable vital details with faster scanning, making them more useful for detecting hemorrhage and stroke. Note that in other modalities, for example, MR, a single series can contain multiple planes of reconstruction (e.g., multiplanar localizers) but this is not the case in CT. The four commonly used MRI modalities are T1-weighted (T1), T2-weighted (T2), T1-weighted with gadolinium contrast enhancement (T1-ce), and Fluid Attenuated Inversion Recovery (FLAIR) [12] as shown in Fig 1.



(b) (c) (d)

Fig 1: Brain images with various slices (a) T1 (b) T1 ce (c) Flair (d) T2

A few exploration works have been done over the most recent twenty years in the field of clinical picture combination. In [13] synopsis of the much comprehensively used pixel-level picture combination techniques and comments about the general characteristics and downsides are presented. Explicit pressure was set on multiscale-based strategies. Barely any executions gauge functional for pixel-level picture blends was also tended to. Singh and Khare[14] proposed a Repetitive Wavelet change (RWT and R-DWT) for the picture combination technique in the multimodal clinical pictures. In their technique, they found that the shift-invariance of the R-DWT produces quality picture combinations on CT, MRI, and PET clinical pictures, and the outcomes were drawn utilizing shared data and strength measurements [15]. An upgraded multimodality clinical picture combination was proposed by Bhateja et al. [16], that additionally involved a multiscale joint disintegration system (MJDF) and shearing channel (SF). The last combination results were acquired by directional coefficients and the union of the intertwined low-pass layers, showing further developed picture combinations in the clinical space. As indicated by Bhatnagar et al. [17], strategies for picture combination are for the most part dependent on a multi-goal examination (MRA) that is fit for decaying pictures into different areas at assorted measures. In their paper, they presented a combination framework because of wavelet change that melded clinical CT and MRI pictures as per the MRA norms, utilizing difference and modulus maxima as two quality significant parts. Their tests were generally uplifting and created outcomes for picture combinations that were quantitatively and quantitatively gotten to the next level. In [18] uniform-based picture combination calculation was introduced where the information pictures were partitioned into blocks. The perfection of each square is registered using the difference between the squares. Also, unique pixel-based calculations were tried and Peak Signal to Noise Ratio (PSNR) is used as an evaluation parameter. Kusuma and Murthy [19] utilized coordinated various information sources including multimodal clinical pictures, presuming that picture combination sturdily further develops the data content and unwavering quality. Practically intertwined multimodal pictures ought to be liberated from any antiquities. In addition, it should not wipe out any relevant data from the first information. In their paper, another method called Shearlet Transform (ST) is utilized on pictures by utilizing the Singular Value Decomposition (SVD) for the improvement of picture data substance. In [20] the specialists suggested a staggered combination of clinical pictures using wavelet change. In his proposition, the locales are fragmented and utilized as essential highlights for the portrayal and recovery of information amid pictures and a district contest-based level set division as opposed to wavelet change.

Different diseases occur due to various disorders that affect the blood supply, or blood vessels to the brain. Brain image fusion presumes a dynamic job in medical imaging applications by helping the radiologists for detecting the variation in CT and MR images. The different picture combinations of CT and MR images of the brain have been executed

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and are assessed for the proposed algorithm. In this paper, the authors have proposed the Ridgempirical Transform technique. In this technique effects of various pre-processing techniques were analyzed on the CT and MR brain images. Ridgelet Empirical Wavelet Transform (EWT) is used to extract the filter banks which are fused by the discrete wavelet transform (DWT) technique. The images are reconstructed by applying Inverse EWT and the Support Vector Machine (SVM) is applied as a classification algorithm. The authors have worked on an online dataset of the same patient but will try for real-time images. To validate the proposed model authors have used fused CT-MR images.

The paper comprises as: section 2 explains the methods where pre-processing techniques are applied to CT & MR images. Different filter banks are evaluated using Ridgelet EWT and are fused & classified. Section 3 shows the results of the effect of pre-processing, fused filter banks, and classification. Section 4 explains the concluding remarks followed by future work.

Methodology

In this paper, the authors have suggested an algorithm "Ridgemprical Transform" which are shown in Fig 2.

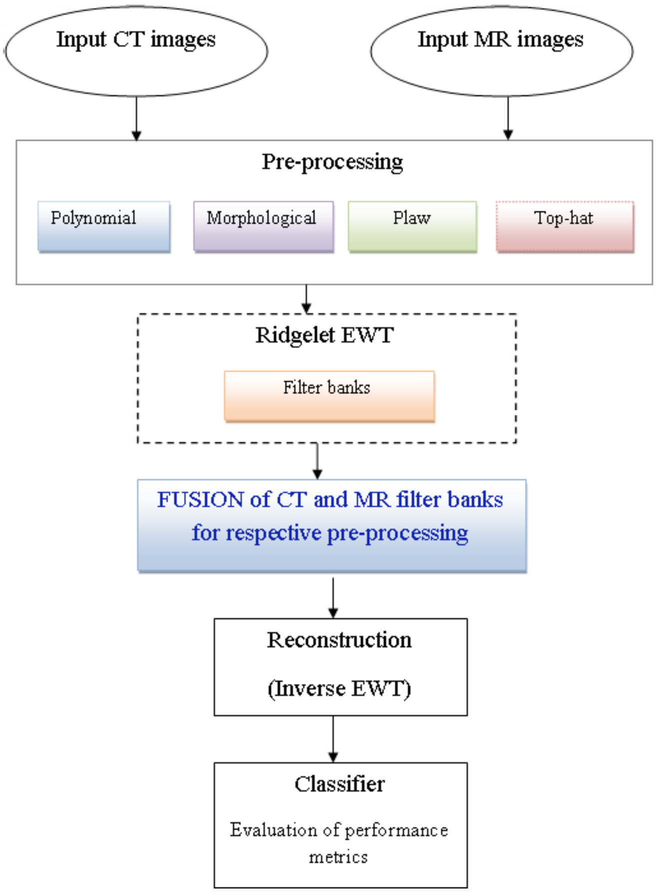

Fig 2: Ridgemprical Transform

The four techniques namely plaw, polynomial, morphological, and top-hat transforms are used to preprocess the CT and MR images used for the detection of brain tumors. The Ridgelet EWT [21, 22]filter banks were extracted which were fused for different pre-processed images. The DWT is used as the fusion algorithms [23 -26] which were reconstructed and classified using a Machine learning algorithm [27, 28, 29]. For the analysis, the online Kaggle dataset https://www.kaggle.com/datasets/darren2020/ct-to-mri-cgan has been used. All the simulations were carried out in MATLAB 2019b software.

Pre-processing is the initial step of Image processing to improve the quality of the images.

This process helps in removing the noise, eliminating variations that occur due to the acquisition of an image, improve classification accuracy. The testing and training time increases for the large dataset, to improve such a problem the unnecessary data was removed. There are different types of pre-processing techniques but in this paper, the authors have used plaw, polynomial, morphological and top-hat transforms. Polynomial Fitting is a capable technique. It works by fitting the values in each instance attribute with a polynomial and then stretching the resulting polynomial to fit the largest-sized data piece. Like for 10 data values $(0, v0)$, $(1, v1)$, ... , $(09, v09)$; 9th coefficient of degree [0, 9] unique polynomial is solved as $f(x) = a.\ x09 + b.\ x08 + c.\ x07 + \cdots + w.\ x2 + y.\ x1 + z.\ x0$ given that $f(0) = v0$, $f(1) = v1$ ... $f(09) = v09$. In the Morphological approach, closing and opening transforms are employed to segregate dark (closing) and bright (opening) in images. Top-hat transformation is an operation that extracts details and elements from an image. White and black are two different types of top hat transforms. The black top-hat transform is the difference between the closing and the input image while the white top-hat transform is it's dual. EWT breaks down an image or signal or a picture on wavelet tight approaches that are constructed adaptively. The vital benefit of this experimental methodology is to hold together some data that ought to be spitted on account of channels [30]. This property of EWT is utilized in the fusion of images combination to work on the value of the intertwined picture. In EWT, a bunch of wavelets is worked by adaption from the handled sign. There are four categories of EWT technique, ridgelet wavelet transform was used in this paper. The evaluation of filter banks is shown in Fig 3.

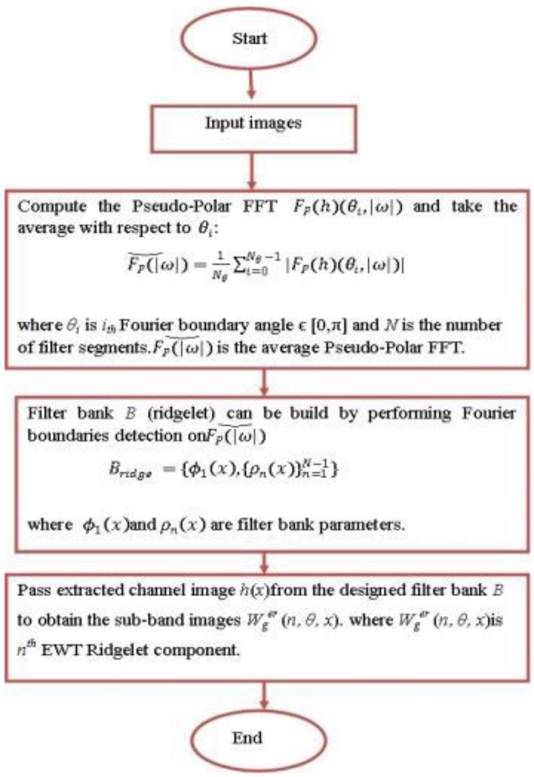

Fig 3: Steps for Ridgelet EWT

The filter banks are fused [31, 32] using Ridgelet EWT which was classified using the Machine learning technique [33]. Machine learning is useful for pattern recognition, if allowed access to patient data; it can notice patterns that would be missed by human doctors, which could be used to predict if a person is at risk for a disease that would not have been anticipated by a doctor.

Results and Discussion

Image processing is a technique that converts the image into digital form so that useful informationcan be extracted, the enhanced image can be obtained, and different operations can be performed. Different transformations like sharpening, smoothening, stretching, and contrasting are applied to the input image. In this paper, the authors have used CT and MR brain images from an online dataset. The brain is a many-layered many-noded recurrent neural network. Recurrent here is used in contradistinction to feed-forward and indicates that once the network transforms its inputs, the transformed result can be fed back through the network and further modify the network. The brain is wired so that firing patterns are transmitted in both directions between various neural structures. The images were pre-processed using four different techniques namely poly, plaw, morphological and top-hat transforms. Authors have worked on different images of the data set. Due to the constraint of space authors have shown the results of 5 images only. Figs 4 and 5 show the filter banks and spectrum of five MR and CT images for different pre-processing techniques respectively. The image boundaries of CT and MR images for various pre-processing techniques using Ridgelet EWT are evaluated and tabulated in Table 1.

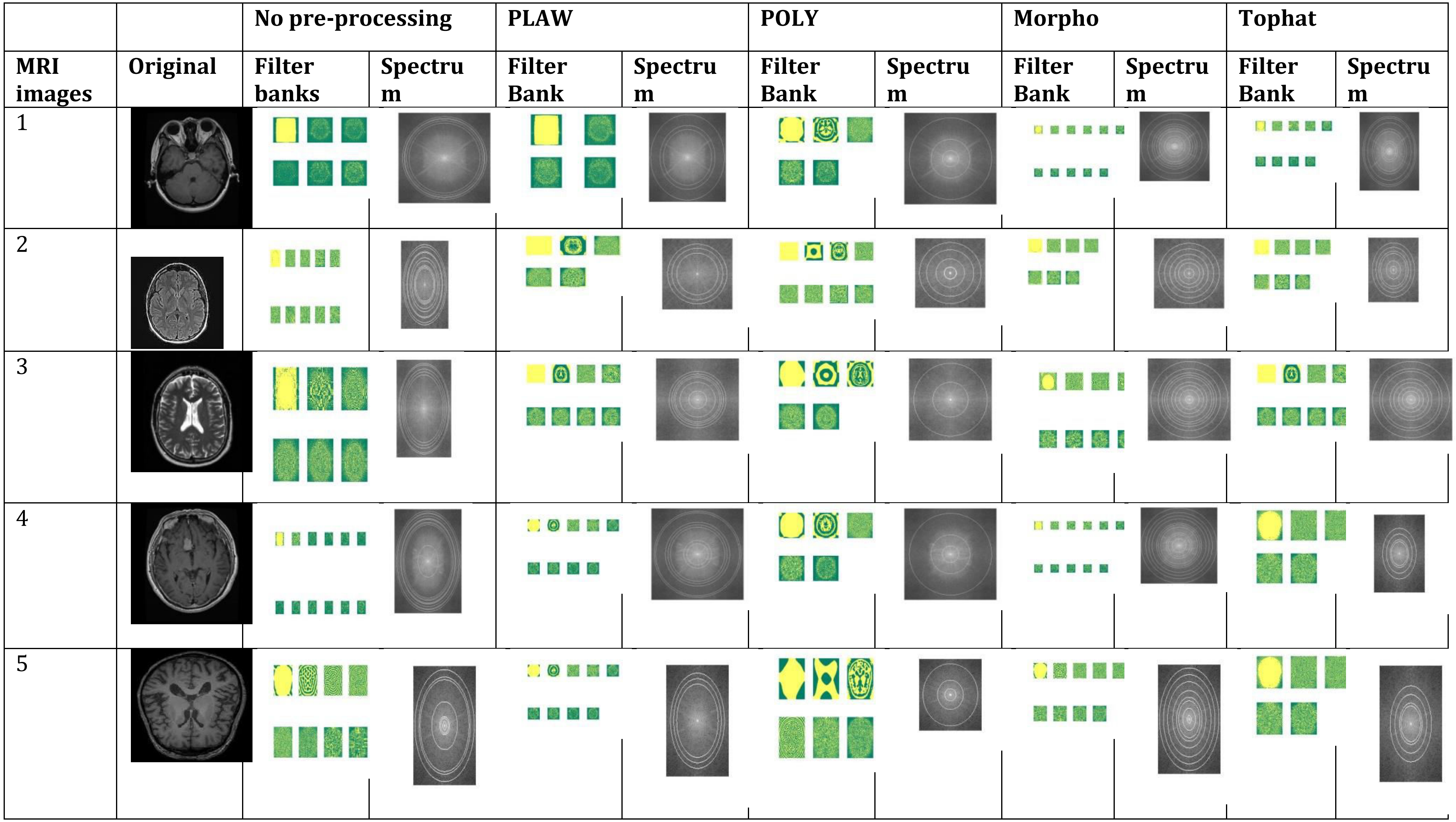

Fig 4: Filter banks and spectrum of MR images for different pre-processing techniques

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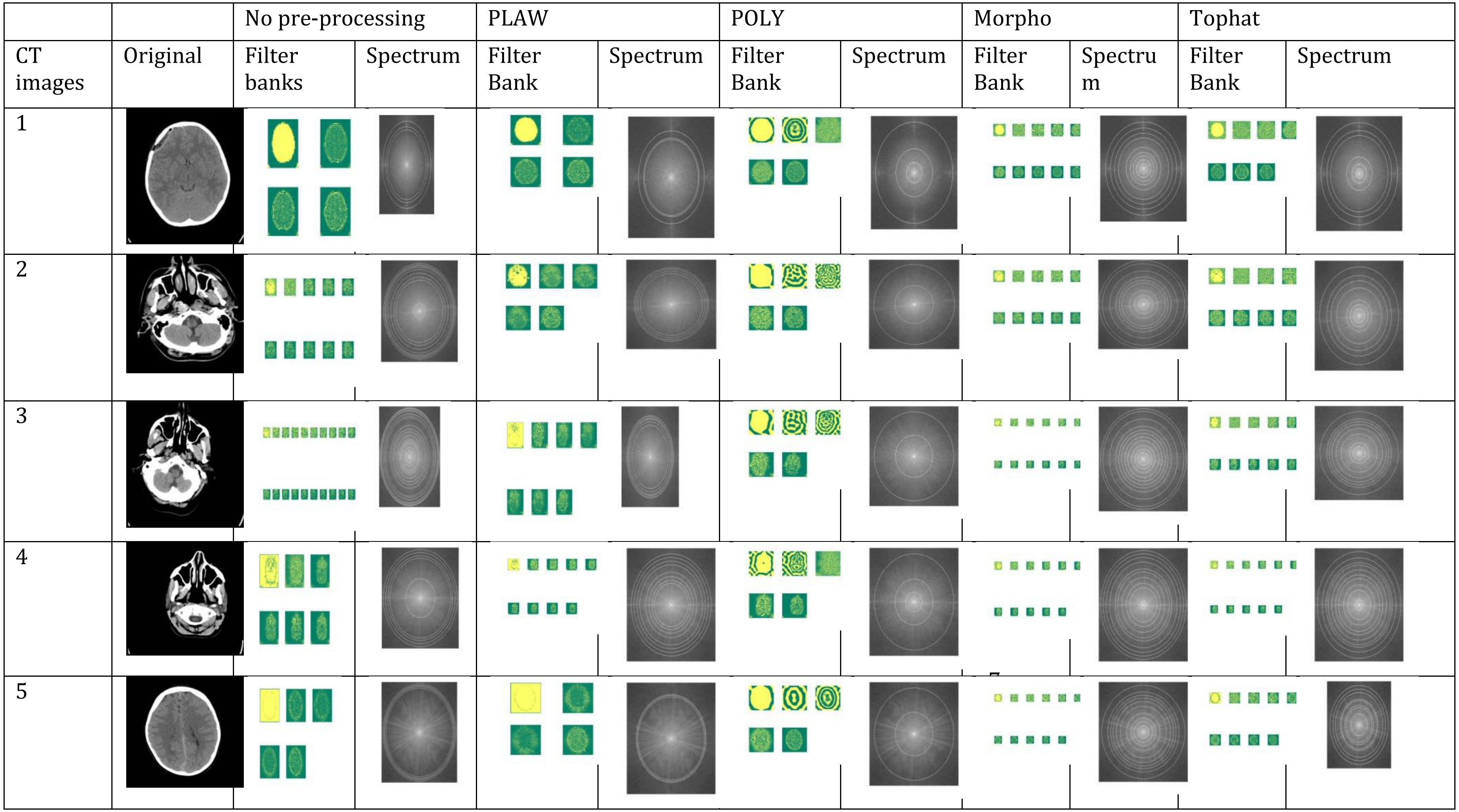

Fig 5: Filter banks and spectrum of CT images for different pre-processing techniques

Table 1: Image boundaries of CT-MR images

CT					MR					CT					MR				
Tophat										plaw									
0.265	0.404	0.141	0.288	0.803	0.263	0.389	0.323	1.288	0.995	2.184	1.982	1.209	2.356	1.982	1.967	0.042	0.027	0.031	0.047
0.517	0.644	0.441	0.816	1.264	0.668	0.903	0.664	1.497	1.150	2.350	2.203	1.374	2.436	2.264	2.044	1.891	0.682	0.736	2.131
0.923	0.895	0.687	1.122	1.417	0.846	1.640	0.960	2.030	1.633	2.497	2.362	1.577	2.491	3.031	2.417	2.335	1.355	0.957	2.442
2.097	1.601	1.288	1.472	1.754	1.607	1.876	1.328	2.325	2.115	2.602	2.418	1.829				2.711	1.714	1.871	2.768
2.373	2.006	1.656	1.681	1.859	1.816	2.251	1.606	2.466			2.516	2.240					1.831	2.031	
2.808	2.313	1.938	1.957	2.350	2.319	2.696	2.190	2.748			2.589	2.442					1.993	2.209	
	2.816	2.123	2.221	2.595	2.681		2.405					2.651					2.190	2.872	
		2.294	2.362	2.871	2.816		2.962					2.853						2.982	
		2.785	2.632																
			2.982																
CT					MR					CT					MR				
poly										morpho									
0.048	0.043	0.049	0.074	0.043	0.049	0.042	0.036	0.049	0.047	0.314	0.350	0.387	0.2089	0.399	0.221	0.445	0.287	0.571	0.218
0.565	0.086	0.074	0.577	0.061	0.558	0.070	0.072	0.571	0.078	0.527	0.650	0.595	0.963	0.663	0.540	0.973	0.745	0.908	0.653
1.334	1.344	1.331	1.344	1.338	1.338	0.528	1.355	1.344	0.560	0.768	0.982	0.822	1.209	0.877	0.693	1.307	1.086	1.055	1.089
2.823	2.823	2.823	2.823	2.823	2.823	0.570	2.818	2.823	1.322	0.962	1.516	1.111	1.528	1.184	0.939	1.752	1.355	1.540	1.306

						1.307			2.815	1.266	1.712	1.331	1.841	1.632	1.399	2.252	1.723	1.712	1.695
						2.155				1.827	1.939	1.559	2.013	1.933	1.620	2.766	1.894	1.859	2.224
						2.822				2.112	2.368	1.749	2.393	2.154	1.847		2.082	2.227	2.644
										2.417	2.884	1.982	2.651	2.326	2.031		2.397	2.485	3.048
										2.779	3.111	2.418	2.853	2.534	2.448		2.962	2.749	
												2.878	3.043	2.958	3.031			3.117	
												3.043							

Table 1 tabulates the image boundaries of Individual CT and MR images considering various pre-processing techniques. In the table when no-pre-processing is applied, plaw, poly, and morpho transform results have been tabulated. Likewise for top-hat transforms results have been evaluated. The filter banks of CT and MR images are fused and some of the combinations are shown in Fig 6.

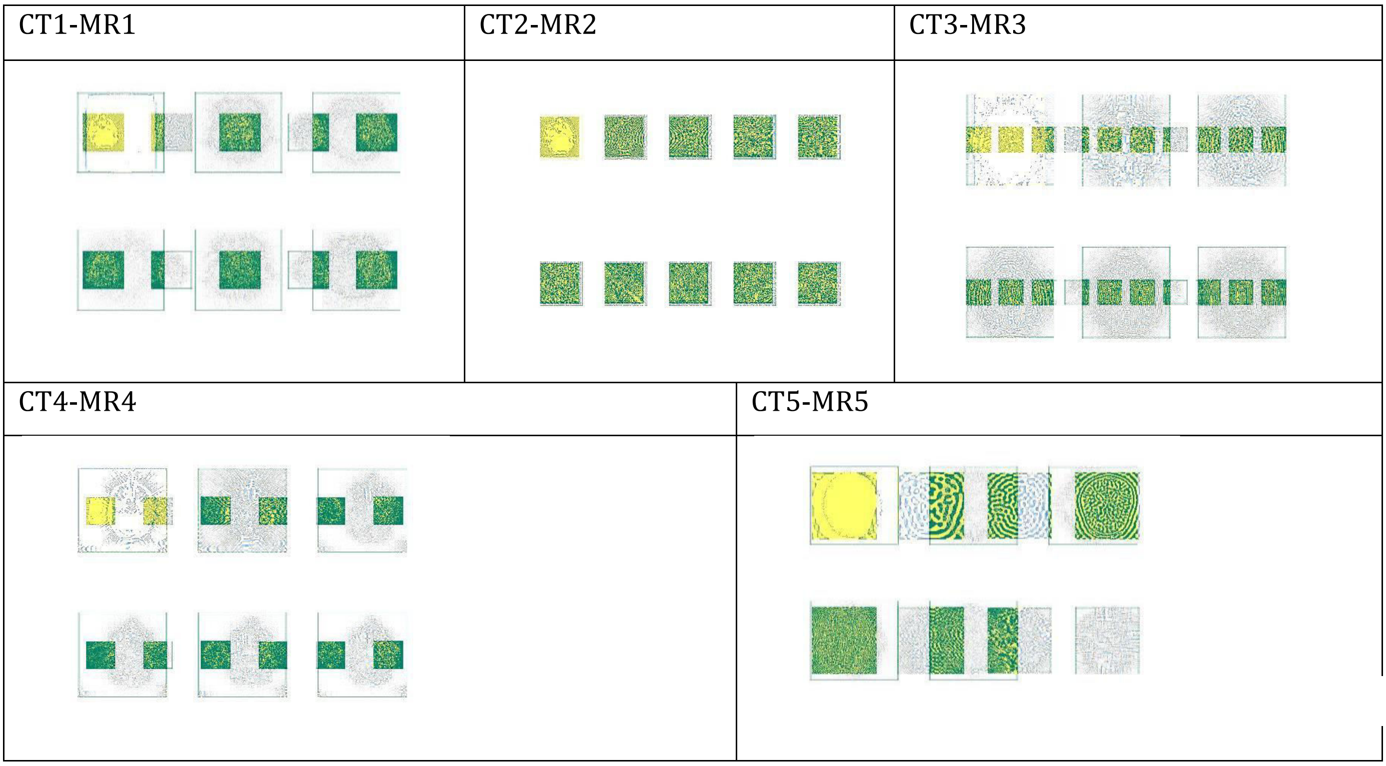

Fig 6: Fused Filter bank of CT & MR image

The images are classified using an SVM classifier and the accuracy is tabulated in Table 2.

Table 2: Evaluation parameters for various pre-processing techniques

Pre-processing Technique	Accuracy
None	79.4%
Plaw	80%
Polynomial	82.6%
Morphological	86.5%
Top-hat	89.5%

89.5% accuracy is obtained using the Top-hat pre-processing technique with SVM classification which results in a better place for other pre-processing techniques. 11.5% improvement has been achieved when no pre-processing technique is applied over the top-hat transform. The authors have validated the proposed algorithm by considering the fused CT-MR image, which is pre-processed using the top-hat pre-processing technique, evaluated its filter banks, and classified using SVM. 92.1% accuracy is obtained for the fused CT-MR image.

Conclusion and Future Work

Image processing is used for analyzing and manipulating images to improve their quality. Imageprocessing let us know about exact quality of the image just by giving some important data that is pixel and co-ordinate of the image. Medical image fusion is the most common way of blending various pictures from numerous imaging modalities to acquire an intertwined picture with a lot of data for expanding the clinical materialness of clinical pictures. In this paper, the authors have used CT & MR images of the brain considered from the online dataset. The different pre-processing techniques were applied to the images and their filter banks and spectrum were evaluated. The filter banks are evaluated for Ridgelet EWT which was fused and classified using SVM. 89.5% accuracy is obtained by employing the top-hat transform technique. 11.5% improvement has been achieved when no pre-processing technique is applied over the top-hat transform. The authors validated the model on the fused CT-MR images and 92.1% accuracy is obtained. In the future author will try other EWT techniques and classification algorithms.

References

Aggarwal JK, "Multisensor fusion for computer vision." Springer Science & Business Media 99 editor (2013).

Salau AO, Jain S, Eneh JN, "A review of various image fusion types and transform", Indonesian Journal of Electrical Engineering and Computer Science, Vol. 24, No. 3, December 2021, pp. 1515-1522

Pal Bandana, Mahajan Surya, Jain Shruti, "A Comparative Study of Traditional Image Fusion Techniques with a Novel Hybrid Method", International Conference on Computational Performance Evaluation (ComPE) North - Eastern Hill University, Shillong, Meghalaya, India. Jul 2-4, 2020, pp 820-825.

Mitchell, Harvey B. Image fusion: theories, techniques and applications. Springer Science & Business Media, 2010. https://doi.org/10.1007/978-3-642-11216-4_2.

Pal Bandana, Mahajan Surya, Jain Shruti, "Medical Image Fusion Employing Enhancement Techniques", 2020 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE), Bangladesh, Dec 26-27, 2020.

Jain S., Sachdeva M., Dubey P., Vijan A. (2019) Multi-sensor Image Fusion Using Intensity Hue Saturation Technique. In: Luhach A., Jat D., Hawari K., Gao XZ., Lingras P. (eds) Advanced Informatics for Computing Research. ICAICR 2019. Communications in Computer and Information Science, vol 1076. Springer, Singapore, pp 147-157.

Pohl, Christine, et al. "Multimodal medical image fusion in cardiovascular applications." Medical imaging technology.Springer, Singapore, 2015. 91-109. https://doi.org/10.1007/978-981-287-540-2_4

Wu, Dingbing, Aolei Yang, Lingling Zhu, and Chi Zhang. "Survey of multi-sensor image fusion."In Life system modeling and simulation, pp. 358-367. Springer, Berlin, Heidelberg, 2014.https://doi.org/10.1007/978-3-662-45283-7_37

Vijan A, Dubey P, Jain S, Comparative Analysis of Various Image Fusion Techniques for Brain Magnetic Resonance Images, International Conference on Computational Intelligence and Data Science (ICCIDS 2019), Procedia Computer Science 167 (2020) 413–422.

Amini, Nasrin, E. Fatemizadeh, and Hamid Behnam. "MRI-PET image fusion based on NSCT transform using local energy and local variance fusion rules." Journal of medical engineering & technology 38, no. 4 (2014): 211-219.

Prakash, Om, and AshishKhare. "CT and MR images fusion based on stationary wavelet transform by modulus maxima." In Computational vision and robotics, pp. 199-204.Springer, New Delhi, 2015.

Dogra J; Jain S ; Sood M, "Gradeint based kernel selection technique for Tumor Detection and Extraction from Medical Images using Graph Cut", IET Image Processing , vol. 14, no. 1, pp. 84 - 93, January 2020

Yang, Bo, Zhong-liang Jing, and Hai-tao Zhao. "Review of pixel-level image fusion." Journal of Shanghai Jiaotong University (Science) 15, no. 1 (2010): 6-12. https://doi.org/10.1007/s12204-010-7186-y

Singh, Rajiv, and AshishKhare. "Redundant discrete wavelet transform based medical image fusion." In Advances in signal processing and intelligent recognition systems, pp. 505-515. Springer, Cham, 2014. https://doi.org/10.1007/978-3-319-04960-1_44

Kaur, Rajveer, and ErGurpreetKaur. "Medical image fusion using redundant wavelet based ICA co-variance analysis." Int. J. Eng. Comp. Sci 4 (2015): 28. https://doi.org/10.18535/ijecs/v4i8.45

Bhateja, Vikrant, Himanshi Patel, AbhinavKrishn, AkankshaSahu, and Aimé Lay-Ekuakille. "Multimodal medical image sensor fusion framework using cascade of wavelet and contourlet transform domains." IEEE Sensors Journal 15, no. 12 (2015): 6783-6790. https://doi.org/10.1109/JSEN.2015.2465935

Bhatnagar, Gaurav, QM Jonathan Wu, and Zheng Liu. "A new contrast based multimodal medical image fusion framework." Neurocomputing 157 (2015): 143-152. https://doi.org/10.1016/j.neucom.2015.01.025

Vadhi R, Kilari V, Samayamantula S. Uniform based approach for image fusion. InInternationalConference on Eco-friendly Computing and Communication Systems 2012 Aug 9 (pp. 186-194). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-32112-2_23

Kusuma, J., and K. N. Murthy."Fusion of medical image by using STSVD—a survey."Int J Eng Res Gen Sci 3 (2015): 571-577. https://doi.org/10.1007/978-981-10-3156-4_7

Bindu, C. H., and K. Satya Prasad. "Automatic region segmentation and variance based multimodal medical image fusion."

In Cognitive science and health bioinformatics, pp. 57-63. Springer, Singapore, 2018.https://doi.org/10.1007/978-981-10-6653-5_5

Kaushal S, Sharma S.D, Jain S., "Empirical Wavelet Transform Based Classification of Glaucoma from Retinal Fundus Images", Journal of Global Trends in Pharmaceutical Sciences 9(3),5887-5897, 2018.UGC no: 46113

Jain S, Salau A.O., Detection of Glaucoma using Two Dimensional Tensor Empirical Wavelet Transform, SN Appl. Sci. (2019) 1: 1417.

Cui, Zhiming, Guangming Zhang, and Jian Wu. "Medical image fusion based on wavelet transform and independent component analysis."In 2009 International Joint Conference on Artificial Intelligence, pp. 480-483.IEEE, 2009.

Krishn, Abhinav, Vikrant Bhateja, and AkankshaSahu. "Medical image fusion using combination of PCA and wavelet analysis."In 2014 international conference on advances in computing, communications and informatics (ICACCI), pp. 986-991.IEEE, 2014.

Chavan, Satishkumar, AbhijitPawar, and Sanjay Talbar.

"Multimodality medical image fusion using rotated wavelet transform." In International Conference on Communication and Signal Processing 2016 (ICCASP 2016), pp. 616-624.Atlantis Press, 2016.

SatyaPrakash, and SachinYadav."Image fusion using hybrid methods in multimodality medical images." Medical & biological engineering & computing 58.4 (2020): 669-687.

Salimi-Khorshidi, Gholamreza, GwenaëlleDouaud, Christian F. Beckmann, Matthew F. Glasser, LudovicaGriffanti, and Stephen M. Smith. "Automatic denoising of functional MRI data: combining independent component analysis and hierarchical fusion of classifiers." Neuroimage 90 (2014): 449-468.

Nirmala, D. Egfin, A. Bibin Sam Paul, and V. Vaidehi. "Improving independent component analysis using support vector machines for multimodal image fusion." (2013).

Prashar N, Sood M, Jain S, “A Novel Cardiac Arrhythmia Processing using Machine Learning Techniques”, International Journal of Image and Graphics. 20(3), 2050023(17 pages), 2020

Jamwal A, Jain S. "Evaluation of Correntropy Features for Normal/Glaucoma Images Employing Ridgelet Empirical Wavelet Transform" , 2022 IEEE Delhi Section Conference (DELCON), 2022

Oliveira FP, Tavares JMR (2014) Medical image registration: a review. Comp Methods Biomech Biomed Eng 17(2):73–93

Liu, Xingbin, Wenbo Mei, and Huiqian Du. "Detail-enhanced multimodality medical image fusion based on gradient minimization smoothing filter and shearing filter." Medical & Biological Engineering & Computing 56, no. 9 (2018): 1565-1578. https://doi.org/10.1007/s11517-018-1796-1

Jain S, “Computer Aided Detection system for the Classification of Non Small Cell Lung Lesions using SVM”, Current Computer-Aided Drug Design, 16(6), 2021, pp 833-840.