International Academic Institute for Science and Technology

International Academic Journal of Science and Engineering
Vol. 8, No. 4, 2021, pp. 29-33.

ISSN 2454-3896

International Academic Journal of Science and Engineering

www.iaiest.com

Medical Image Fusion & Classification Of Tumor Cells Using Deep Learning

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Abstract

Clinical "image fusion" is a complex course of Consolidating and enlisting different image from Single or numerous examining methods that can envision the human body for conclusion and tracking down the idea of infections and for treatment purposes. This interaction is applied to upgrade the nature of the images and furthermore to diminish the consistency and overt repetitiveness. Through clear sensing and analysis of the fusion, experts may definitely identify the precise location of the tumor in any part of the brain. Thus, this study presents a deep learning-based fusion-based categorization model with the following stages: The process involves gathering data from brain MRI and CT scan images using tools like REMBRANDT and Kaggle, fusing MRI and CT images using variational mode decomposition (VMD) and local energy maxima (LEM), preprocessing the fused medical image using enhanced CLAHE and non-local mean filter (NLMF) to improve image quality, using a convolutional encoder to extract features, and finally using a Baysian autoencoder to classify multimodal images. Experimental results show that proposed model outperforms better than other state-of-art models under various measures (accuracy:0.95, specificity:0.97, sensitivity:0.97).

Keywords: Brain Tumor, Baysian Autoencoder, Classification, CT, CLAHE, Convolutional Autoencoder, PSO, VMD.

DOI:10.71086/IAJSE/V8I4/IAJSE0828
Received: 10 September 2021/Revised: 12 October 2021/Accepted: 09 November 2021/Published: 31 December 2021

Introduction

The Medical analysis and its applications are extremely challenging and complicated in many versions. By the way, one of the most challenging domain in the medical field is human brain analysis. Themanual process by domain specialist is more time consuming task. -Still, there is need for efficient technique. In order to detect brain tumors, the MRI and CT scans are combined in this article, opening the door to effective analysis. The process of combining two or more medical images to extract useful information for medical assessment is known as medical image fusion. They can more efficiently identify normal and abnormal regions ofthe human body. The unpredictable cases in medicalfield mostly comes under in tumor detection. This paper involves the detection of the brain tumor from the fused image. The combination of anomalous cell in brain causes brain tumor (Zhou et al., 2019). Therefore, from the fused image of MRI and CT, the more detailed information on brain tumor is obtained. Thus,there are various stages in this process such as image pre- processing, fusing of image and clustering for segmentation. Finally, the detected tumor is validated in three parameters like its sensitivity, specificity and accuracy. From the extracted morphological structure of tumor radiologist can easily identify its location, shape, size and its intensity.

The brain, which is made up of soft tissues that are spongy and non-replaceable, is the focal point of the neurological system (Zhou et al., 2019). Many disorders, including brain tumors, can have an impact on it. Seizures, recurrent headaches, memory loss, and problems with coordination and speaking are some of the main signs of a brain tumor. Brain tumors can be categorized according to their growth rate, place of origin, and stage of progression (Algarni, 2020). Brain tumors are categorized by the World Health Organization (WHO) into grades I through IV (Xiao et al., 2020). Some specific characteristics of brain tumors are described by the grade that has been assigned. These characteristics are linked to particular results.

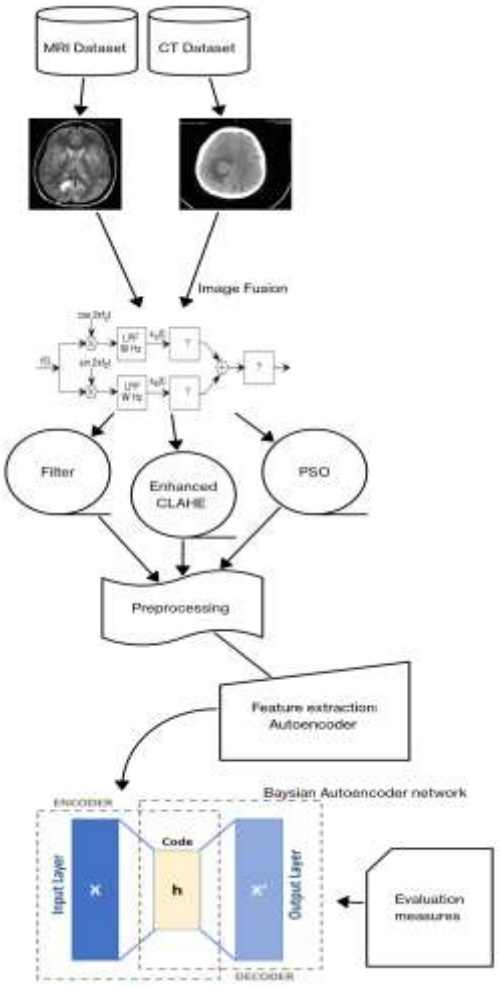


Fig. 1: Overall Architecture of Proposed Framework

Methodology

The general architecture of the suggested framework is depicted in Fig. 1, with the following stages: supplying sufficient data to the classifier to enable it to learn for any deep learning analysis. So, here for performing the fusion, use of MRI and CT image of tumor data is been collected from REMBRANDT and Kaggle dataset. These now will be fused using frequency domain technique to get the multi modal image fusion for performing further analysis of tumor identification. Therefore, variational mode decomposition (VMD) and local energy maxima (LEM) are utilized to conduct image fusion. Once these image are being fused, they will undergone for preprocessing for improving the quality of fused image using filters and CLAHE. Then with the help of feature extraction, quintessential edge features are extracted using convolutional Autoencoder and and finally classifies tumor using Baysian Autoencoder network from the fused image (Zhang et al., 2021).

Data Collection

For this tumor identification, especially this research work use of brain tumor dataset is been taken and also for image fusion, use of MRI and CT image is shown below;

VMD-Based Image Decomposition: Conventional decomposition techniques like wavelets, BEMD, and EWT have a number of issues, including mode-mixing and border distortions. We might not get the right fusion outcome with these problems. We used VMD, a strong adaptive decomposition technique, to emphasize important details as sub-images in order to solve these issues. The VMD is used in texture decomposition and image denoising (Rajalingam & Priya, 2018). VMD is an adaptive and non-stationary signal processing method. In contrast to EMD and its variations, VMD breaks down the signal or image into bandlimited sub-bands according to its frequency content and is not a recursive analysis method. In this study, unique and meaningful IMFs are extracted from the source images (MRI and CT) using VMD. The two main issues with the aforementioned transform domain methods—mode-mixing and boundary distortions—are lessened by the derived IMFs. This VMD decomposition allows us to obtain information about significant edges. The input photos were then broken down into six IMFs, as shown in Fig. 2.

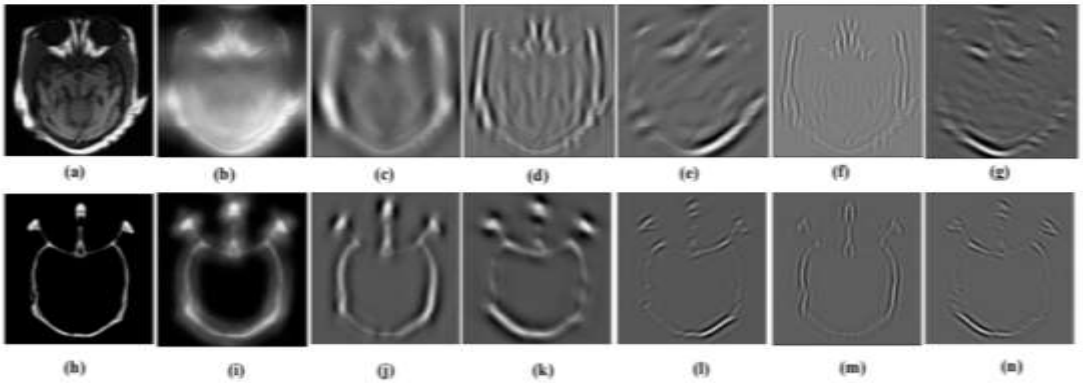


Fig. 2: IMFs Obtained after VMD Decomposition: (a) MRI Image, (b) and (c–g) are Approximation and Detail Images of (a), Respectively. (h) CT Image, (i) and (j–n) are Approximation and Detail Image (h)

Fig. 2 shows that while the other IMFs include line and edge information, the first IMF ((b) and (i)) catches important information from the source images. Fig. 3 shows that the visual features become less important as the mode number rises.

One unsupervised machine learning algorithm based on artificial neural networks is autoencoder. Reconstructing output close to the original input is the goal of autoencoder training (Sangeetha Francelin Vinnarasi et al., 2021). A hidden layer, which typically has a dimension smaller than the input, an input layer, and an output layer—which has the same number of dimensions as the input layer—make up an autoencoder. Fig. 3 illustrates an autoencoder in its most basic form.

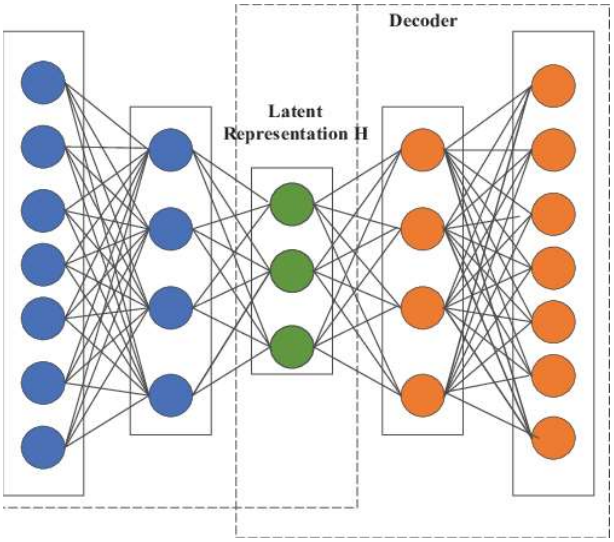


Fig. 3: Autoencoder Network for Feature Extraction

The Bayes Net approach, or BAE, builds a generative model. In order for the network to predict each component of a given datum from the others, it determines the network topology and modifies the conditional probabilities (Guo et al., 2018). It uses the features of the provided training data to extract hidden variables. By acting like a Bayes Net, the networks built by BAE are able to identify characteristics using belief propagations. A two-layer Bayes Net is initially built by BAE as a directed full bipartite graph with a hidden layer of parent variable nodes and a visible layer of child variable nodes. In order for the network to predict input data, BAE modifies its parameters and removes some links (Kaur & Singh, 2021).

Results and Discussion

Hardware specifications such as the Ryzen 5/6 series CPU, NV GTX, 1 TB, and Windows 10 OS are used in the implementation, along with software specifications such as Google Collaboratory, an open source Google environment for deep learning model development, and Pytorch, an open source Python library for deep learning model building. The overall analysis under accuracy, sensitivity, and specificity is shown in Table 1. Table 1 is graphically represented in Fig. 4, where the suggested model performs better because of its simple yet intricate encoding and decoding structure. Overall Fusion Strategy Comparison Analysis shown in Fig. 5.

Table 1: Overall Analysis Under Accuracy, Sensitivity, Specificity

Models	Accuracy	Sensitivity	Specificity
State-of-the-art models	85	91	94
Proposed model	95	97	97

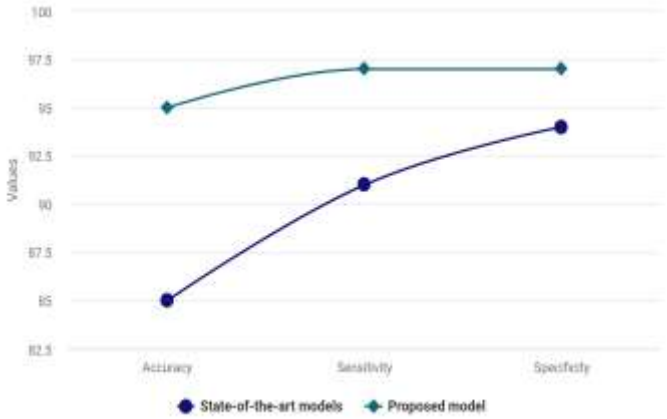


Fig. 4: Models vs Accuracy, Sensitivity, Specificity

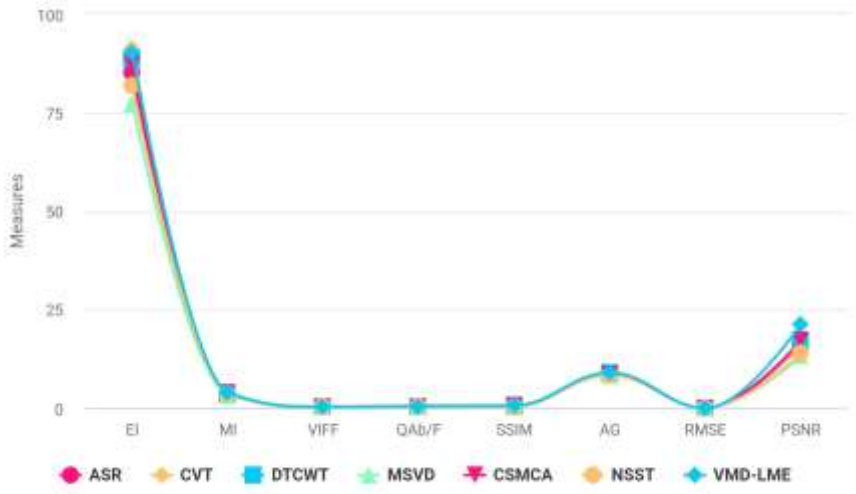


Fig. 5: Overall Fusion Strategy Comparison Analysis

Conclusion

In this study, we suggested a multi-modular clinical image fusion system that combines CT and X-ray clinical images using VMD and LEM. Using a flexible disintegration process, VMD, large IMFs are extracted from the original images. A few details of the original images can be preserved by this decomposition interaction. However, these distinctions are insufficient to meet radiologists' clinical needs. Therefore, as a basic precaution during clinical image detection, we used an LEM combination rule to protect integral data from IMFs. With the aid of a deep learning classifier, the merged picture via VMD with above 90% has also been used to diagnose tumors. All research specialists will find this document helpful in delving further into different ways and attempting to create integrated yet sophisticated features to increase efficiency even further.

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