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MRI and CT scan image fusion ML Model for brain tumor detection

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ABSTRACT:

The proposed machine learning model is dedicated in fusion of MRI and CT scan images for better analysis of medical research. The fused image results in efficiently higher results than the existing systems. The proposed model is developed for multimodal image fusion of CT and MRI Scan images. This can be highly used for specific research such as Brain Tumour. The model is expected to have a result of fused image with a minimum measure between pixel-wise difference. For every 200 times once the learning efficiency of the model is increased by 20% in the measure of pixel wise difference.

1. INTRODUCTION

In Clinical research it is necessary to analyse the medical images in order to diagnose it. There are various medical images (such as MRI, CT, PAT and etc.,) used for their particular specifications. Yet despite specifications, CT and MRI scan images are most widely used medical images used for various clinical researches. Therefore, we have proposed a machine learning model that fuses MRI and CT scan multimodal images with the computed parameters like SSIM, PSNR and MSC to determine fused image efficiency.

In this project we have discussed about various methods to improve the quality of the fused image and enhance the model behaviour. 1Rajkumar B proposed to design the model using python and the requirements, 2Monish B worked on the implementation fusion techniques using OpenCV. 3Ilaiyaraja R, 4Shanthosh B J and 5Sharath P assisted in research, analysis of existing models and worked on the literature survey(references).

2. METHODOLOGY

The proposed system uses Deep Learning concept of CNN (Convolution Neural Network) to get a trained machine learning model to efficiently fuse images. In addition, the model is developed using Python and its inbuilt libraries such as TensorFlow, NumPy, scikit-learn, matplotlib, OS and OpenCV.

The CNN architecture of this model uses advanced techniques like residual connections, batch normalization and up-sampling layers with skip connection. At first the shape of the input images (CT and MRI scan images) is specified with width, height and number of channels. Then the image is converted into lower-dimensional representation by key features using the encoder.

Initially a 32-convolution filter of size (3,3) is applied to learn the spatial features, then enabling the model to learn complex patterns by introducing it to non-linearity. Then the model, normalizes the output to improve training stability and speed and reduces the spatial dimensions by half, creating a condensed feature map.

This process is repeated with increasing filters (64-convolution filter and 128-convolution filter) to capture more complex and hierarchical features. When the number of channels increases the spatial resolution decreases, making the feature maps more abstract.

Now up-sampling, the decoder reconstructs the fused image from compressed feature maps by performing transpose convolution, efficiently increasing the spatial resolution. To ensure smooth up-sampling the features are normalized and added with non-linearity. Each layer of the up sampling doubles the spatial resolution.

The final output, is generated considering the image in RGB colours and has 3 channels. The output is scaled pixel values between 0 and 1, best suited for normalized images.

2.1 TensorFlow and OpenCV

The use of TensorFlow and OpenCV are the most essential tools in developing this model. TensorFlow offers variety of advanced deep learning suits and OpenCV offers variety of image fusion suits that enhance the efficiency and structure of the model.

2.2 NumPy

NumPy offers high mathematical computation techniques that can be used with other python libraries. NumPy is used to operate with the images, handling it as 2-dimensional array. We use weighted average method to fuse the CT and MRI images, NumPy is crucial in this part of the model.

2.3 Matplotlib

The final output of the system is consoled using matplotlib, this python library offers top class features to graph our output fused image. We have included the SSIM, PSNR and MSC values to it.

3. PROPOSED SYSTEM VS EXISTING SYSTEM

Traditional methods for medical image processing, such as Principal Component Analysis (PCA), wavelet transform, and other hand-crafted feature extraction techniques, rely heavily on manual intervention and basic algorithms. These methods offer limited resolution and detail preservation, often resulting in moderate accuracy due to restricted feature analysis capabilities. Their dependency on manual processes and classical algorithms makes them relatively slow, with limited scalability and adaptability to new datasets or conditions. Noise filtering in these approaches is basic, leading to a higher likelihood of artifacts in the processed images.

Moreover, traditional methods are sensitive to variations in imaging quality, limiting their reliability and generalizability. Although these techniques are clear and interpretable, they lack the complexity needed for modern medical applications and are best suited for scenarios requiring smaller datasets and straightforward analysis.

In contrast, advanced deep learning methods, such as Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), revolutionize medical image processing with their automated feature extraction capabilities. These methods leverage the power of deep networks to analyse data at high resolutions, preserving structural details and achieving superior accuracy. Deep learning techniques are faster than traditional methods due to automation and the use of GPU acceleration, allowing for efficient processing of large volumes of data. Advanced denoising algorithms embedded within these models further enhance image quality by reducing noise without introducing artifacts. The scalability of deep learning architectures allows them to adapt to diverse datasets and imaging modalities, ensuring robust performance even under varying input conditions. Additionally, they enable seamless integration with diagnostic tools, facilitating real-time analysis and decision-making in clinical settings.

Deep learning models are designed to handle complexity, incorporating explainability techniques to enhance transparency and interpretability. However, these methods require large annotated datasets for training, a challenge offset by their ability to generalize across different clinical scenarios. With modern AI frameworks like TensorFlow and PyTorch, these methods are easily modifiable and adaptable for specific applications, such as analysis and fusion in clinical research. Their robustness and adaptability make advanced deep learning techniques indispensable in modern medical image processing, outperforming traditional methods in accuracy, speed, scalability, and integration.

4. EXPERIMENTAL RESULTS

The input images are CT and MRI images (Fig.1 and Fig.2), these inputs are given as parameters in the convolution function. The output will be a fused image with the computed parameters of SSIM, PSNR and MSC which is tabulated in Table.1.

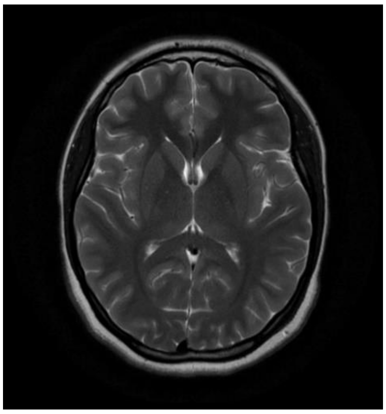

Fig.1 MRI image

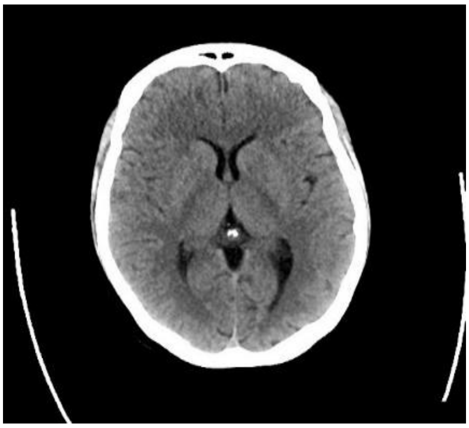

Fig.2 CT Image

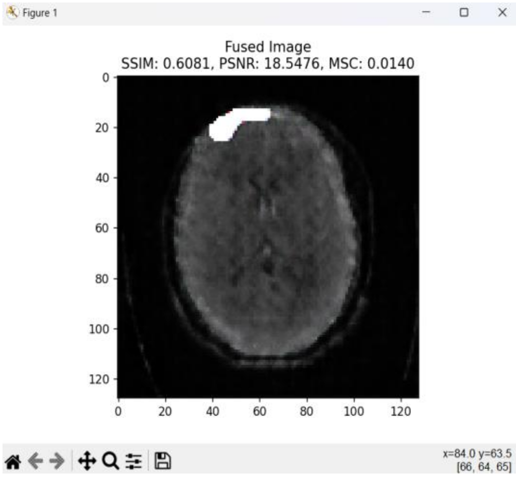

Fig.3 fused image (Epoch:500)

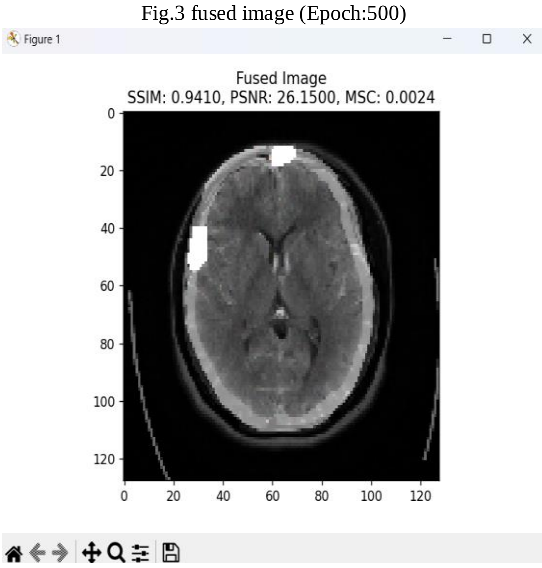

Fig.4 Fused image (Epoch:1000)

The outputs (Fig.3) are displayed using matplotlib. The model is trained for N number of cycles, given as the epoch value. The model should not be trained either underfit or overfit, it should be given the correct number of training cycles as per the input data. For each training cycle the model increases its efficiency, here the loss is decreased significantly.

Table.1 Observed Results

	Epoch : 500	Epoch : 1000
SSIM	0.6081	0.9410
PSNR	18.54	26.15
MSC	0.014	0.002

5. CONCLUSION

The machine learning model is tested with the sample input of Fig.1 and Fig.2 (CT image and MRI image respectively), by adjusting the epoch as 500 and 100 two analytical output have been noted in Table.1 considering structural similarity(SSIM), Noise level in Image (PSNR) and measure of pixel-wise difference (MSC).

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