Chapter 70
Performance Analysis of VGG19 Deep Learning Network Based Brain Image Fusion

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ABSTRACT

Multimodal imaging systems assist medical practitioners in cost-effective diagnostic methods in clinical pathologies. Multimodal imaging of the same organ or the region of interest reveals complementing anatomical and functional details. Multimodal image fusion algorithms integrate complementary image details into a composite image that reduces clinician's time for effective diagnosis. Deep learning networks have their role in feature extraction for the fusion of multimodal images. This chapter analyzes the performance of a pre-trained VGG19 deep learning network that extracts features from the base and detail layers of the source images for constructing a weight map to fuse the source image details. Maximum and averaging fusion rules are adopted for base layer fusion. The performance of the fusion algorithm for multimodal medical image fusion is analyzed by peak signal to noise ratio, structural similarity index, fusion factor, and figure of merit. Performance analysis of the fusion algorithms is also carried out for the source images with the presence of impulse and Gaussian noise.

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INTRODUCTION

With the astonishing development of fast computing technologies and medical imaging systems, health care to mankind has evolved tremendously. The rapid development of the fast computing systems over the decade paves the way for advanced machine learning and deep learning concepts in medical image processing. This development directs medical diagnosis towards e-diagnosis that aids medical practitioners in fast diagnostic procedures. Over the decade, medical image processing has evolved manifold with the help of deep learning networks handling a huge volume of complex data. Deep learning models learn high-level features from the medical dataset without complex feature extraction. The evolution of GPU with computing libraries also makes learning faster. Deep learning networks (DLN) have become more effective for image processing due to the availability of public datasets and optimization techniques. Deep networks have their role in computer-aided diagnosis, multimodal image registration, fusion, segmentation, and classification of a region of interest (ROI), image-guided therapy, image analysis, image retrieval, and so on. Deep networks can be trained for specific clinical applications with the intended dataset, fast computing system, and a huge volume of data. Pre-trained networks can also be used for medical image processing towards specific clinical applications. The deep networks surpass machine learning strategies due to their ability to handle a huge volume of complex data. Various deep learning networks have evolved over the years for different applications. Multiple layers of the neuron, stacked for feature representation, can recognize various possible mappings after effective training with a vast knowledge database. There are different types of deep learning networks with a modification in the basic architecture. Deep neural networks (DNN) have more than two layers to analyze the complex non-linear relationship among the input variables. This network is widely employed for classification and regression-based applications. The accuracy of DNN is good. But, the network is very slow in learning. Convolution neural networks (CNN), consisting of convolution layers, are good for a two-dimensional dataset. CNN has the advantage of fast learning but needs a labeled dataset for classification. Recurrent neural networks (RNN) find applications in natural language processing, speech recognition, and character recognition with good accuracy. RNN is capable of learning sequences and the weights are shared across all neurons. Training for RNN needs a very big dataset and also suffering from gradient vanishing. Deep convolutional extreme learning machine (DCELM) uses Gaussian probability functions for the sampling of local connections between the input variables. Deep Boltzmann machine (DBM) achieves robust inference about the input dataset through top-down feedback and unidirectional connection between the hidden layers. But, this network lacks optimization of parameters for a big dataset. Deep belief network (DBN) uses an initialization process that makes a computationally expensive training process. Each hidden layer in this network acts as visible layers to the next layer in the hierarchy. On the top layers, the two layers have a unidirectional connection. The accuracy of DLN largely depends on the quality and size of the dataset. The success of various DLNs in medical imaging applications are suffered by the non-availability of quality dataset and volume of data. This requirement leads to data annotation which requires extensive time from the medical practitioners. Another trivial factor is the reliability of the annotated dataset that needs to be ensured by multiple expert opinions. Non-availability of sufficient data in certain clinical pathologies and ethical guidelines of the patient data restricts the application of deep learning strategies.

Image fusion is a technique that integrates two or more images from the same modality or from different modalities to yield a composite image of complementary details (Chen et al., 2020). This helps medical practitioners for better diagnosis and reduces human error. Image fusion strategies have also

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