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Medical Image Data Classification Using Deep Machine Learning Techniques and Neural Networks

Dr. J Madhavan[*1], Dr. N. Satheesh Kumar[2], Dr. M. Venkatesan[3], Dr. Bhaludra R Nadh Singh[4], Dr. Bremiga Gopalan[5]

*1Professor, Department of ECE, Bhoj Reddy Engineering College for Women, Vinay Nagar, Hyderabad, Telangana, India.

*2Professor, Department of ECE, PBR Visvodaya Institute of Technology and Science, Kavali, SPSR Nellore, Andhra Pradesh, India

*3Professor, Department of ECE, Visvodaya Engineering College, Kavali, SPSR Nellore,Andhra Pradesh, India

*4Professor, Department of CSE, AVN Institute of Engineering and Technology, Hyderabad,Telangana, India

*5Assistant Professor, Department of ECE, Bhoj Reddy Engineering College for Women, Vinay Nagar, Hyderabad, Telangana, India

ABSTRACT

Healthcare sector is one of the prime and different from other trade. Society expects high priority and highest level of services and care irrespective of money. Presently medical field suffers from accurate diagnosis of diseases, and it create huge loss to society. The prime factor for this is due to the nature of medical data, it is a combination of all varieties of data. Medical image analysis is a key method of Computer-Aided Diagnosis (CAD) frameworks. Customary strategies depend predominantly on the shape, shading, and additionally surface highlights just as their mixes, a large portion of which are issue explicit and have demonstrated to be integral in medical images, which prompts a framework that does not have the capacity to make portrayals of significant level issue area ideas and that has poor model speculation capacity. In this paper we are attempting a medical image data classification technique using hybrid deep learning technique based on Convolutional Neural Network (CNN) and encodes. What's more, we assess the proposed approach on two benchmark clinical picture datasets: HIS2828 and ISIC2017. The proposed algorithm is applied on the considered 2 datasets for performing data classification using deep learning-based CNN and encoders. The proposed model is compared with the traditional methods and the results show that proposed model classification accuracy is better than the existing models.
Keywords : CNN, encoder, medical images, classification

I. INTRODUCTION

Understanding and finding the correct region of interest in medical images helps to correctly diagnose the disease. Image segmentation is one of the prominent steps in analyzing medical images using machine learning algorithms. Traditional image segmentation algorithms always do not give correct result and does not help to dig the region of interest correctly [1]. All anatomical structures depicted in the medical image needs to be correctly segmented. There are range of applications such as surgical planning, anatomical structure modeling and image -based diagnosis where correct segmentation is verynecessary and important. Automatic segmentation methods have been researched earlier but it is also proven that they can give hardly correct results. There can be various reasons like poor image quality, the pathological parameters of the patients differ to a large extent and are inhomogeneous, the predictions made by clinicians also varies. All these varying parameters gives different structure boundary of the image to be segmented. The results of segmentation are incorrect as there is no unanimity in all the above-mentioned functional areas. Although there are methods like augmenting the medical images withuser interactions, but this step seems to be a burdenon the user interactions. As per the researchers a goodsegmentation should have few user interactions. This leads to increase in interaction efficiency. Machine learning tools are generally used to decreases user interaction. Examples of machine learning methods are Gaussian mixture models, GrabCut algorithms etc. There are some extra techniques that are required to be applied on the image like bounding box and scribbles to refine the result. These increases the computational cost. Recently deep learning tools and techniques along with Convolutional inter connected system is used for image dissection [2]. They provide results much faster than what one gets using manual techniques. There are many types of Convolutional Neural Networks used amongst which fully convolutional neural network has gained lots of importance in medical image segmentation. It gives the correct result by providing forward processingonly once and that to at the testing time. Recent improvement on Neural Network technology has been done on two aspects: first overcomes theproblem of reduced imager caused by repeated combination of down sampling and highest pooling. Although certain up sampling layers recovers the resolution easily, this leads to binary like segmentation. The results are of low accuracy. In case of dilated convolutional network, the down sampling layers are replaced and exponential increase of the receptive field happens with no loss of resolution. It always requires a generalized segmentation model which receives further attention. The second aspect enforces inter -pixel dependencies in order to get a temporally correct result. This supports to understand edge details and also reduces unwanted disturbances in pixel differentiation [3]. Another important architecture that has gained immense response in the field of image processing is called as U-Net. It is applied in cell detection from two dimensional to three dimensional images. There are certain Conditional Random Field's used as a step of postprocessing along with segmentation in convolutional neural networks.

II. LITERATURE SURVEY

Typical CNN's such as Google Net, AlexNet, VCG and ResNet were initially analyzed to do image classification tasks [41]. There are certain works earlier that have adapted these networks and progressed on with their pixel classification. Thesenetworks help in pixel labelling, having patch or region-based methods. These networks achieved higher rate of accuracy than the traditional methods.

These networks have certain disadvantages also and that is shown at the time of testing. Fully convolutional network works by considering anentire image as input and gives the result in the form of dense segmentation. There is also a problem of loss of spatial design because of more than one stage of max pooling and also down sampling. To overcome these disadvantages this method uses stack of deconvolution and activation function to up-sample the layers [4]. Inspired by these features of convolutional network and deconvolutional framework, a Ushaped network called U-Net was proposed. The three-dimensional version of this U-Net architecture was specially used for biomedical image segmentation. A similar kind of architecture called V-Net is proposed that is used for segmentation of prostate MRI images. There were certaindrawbacks of successive down sampling and max- sampling [5]. There is certain loss in feature map resolution. So dilated convolution was proposed that would keep safe the architectural parameters of feature maps and thus enhance the receptive field so that it contains larger textual information. In a pile of dilated convolution, object tracing and semanticsegmentation is performed. Enlarged convolution is also used for instance-sensing segmentation and also detects actions from video graphic frames [6]. Convolution network are also used to extract multiple scale features. This is done to improve the segmentation accuracy. Multi scale features are obtained by passing multiple forms of the input image throughout the same network. The features thus obtained can be used is used for pixel classification. The features belonging to each pixel are obtained from two homocentric patches having varying sizes. In case of multi scale images, these are fed at number of stages into a recurrent convolutional network. Another popular use of multiple scale feature is in using the feature maps considering disproportional levels of convolutional neural network. The features from intermediate layers are augmented for the purpose of localization and segmentation. Another procedure in segmentation that is widely used is called Interactive Image Segmentation that is used in various application. The user interactions are varied such as contour-based, click-based and bounding box methods. Scribbles can be also drawn in Graph Cuts, Random Walks, GeoS. However, most of these are used on lower-level features and requires larger amount of user markers. These helps to deal with images having darker profile and equivocal boundaries. There are machine learning tools that are proposed to learn from user markers. These algorithms cannot achieve better dissection accuracy with lesser user communications. But they need to rely upon limited manual features that relies on one's experience. The deep convolutional network has improved interactive segmentation. The convolution neural network has spontaneous feature learning and also shows high performance. Some of the examples are a three-dimensional U-Net that learns from marked images and later on used in not fullyautomatic segmentation [7]. Scribbles are also used to train the CNNs. Deep cut uses user provided boundary box as markings to train the convolutional neural network as required for the segmentation of MRI images. There are procedures which are not fullycommunicative and are also not suitable for testing, as they restrain themselves to accept farther annotationsfor refinement. In case of deep communicative objects selection tools are proposed where images capturedare changed into Euclidean distance maps and then they are added with the input of fully analysis convolutional neural networks. In contrast the geodesic distance transforms and encodes the spatial dimensions and contrasts the sensitivity, though it has not been used for CNNs. Graphical models such as Conditional Reference Fields are immensely used to increase dissection accuracy by using spatial accuracies. In case of spatial regularization, the Potts energy is minimized with minimum max/cut flow algorithm. In the maximum-flow problem mapping is done to provide optimization formulations [8]. They provide segmentation consistency of neighboring pair pixels having similarity in features. In the process to include long distance connections within image segmentation, a totally connected CRF is used. This establishes pair wise potential amongst all images. Theadjacent edge capabilities as defined by a straight mixture of Gaussian Kernels. Other methods include gradient based optimization and integrated output support vector machines and. These are also used to learn from parameters in CRFs. After we have successfully segmented the image, we need to proceed with feature extraction. For feature extraction of medical images there are various deep learning algorithms. Convolutional Neural network can be used for feature extraction. Many researches on feature extraction of medical data deals with making amodel that will analyze the text features of the medical images using convolutional neural network. After we have done the feature extraction, last step as part of image processing, we can go with a classifier toanalyze the features based on their abnormalities. We can use either a convolutional neural network or any traditional classification algorithm for classifying the processed images. There are many states of the art algorithms that can be used for image recognition. It is known that Support Vector Machine algorithm is one of the most common classification algorithms that is used in many medical image processing and [9].

III. PROPOSED SYSTEM

Human Vision and Feedback Mechanism. Although the feedforward convolutional neural network has achieved great success in computer vision tasks, itdoes not have more feedback connections. CNN is a method of simulating human characteristics.However, it has no feedback mechanism. In view of this revelation, this paper considers adding a feedbackconnection model to the convolutional neural network to make the convolutional neural network more humanized to obtain better application effects. rough target-driven feedback control, the accuracy of human detection and recognition of targets is improved in complex scenes. It enables the visionsystem to generate selectivity for neuron responses when processing visual information [39]. In addition, convolutional neural networks have powerful object recognition capabilities [40]. Recent studies have shown that [41, 42] internal neurons of convolutional neural networks for classification purposes can learn to express a variety of visual semantic patterns from massive images, for example, from simple edge features and color features to complex target local features or even complete targets. It shows that the convolutional neural network can segment objects in the image from layers that are simple to complex mode representations. Inspired by the above phenomena, this paper can imitate the working mechanism of visual attention in the deep convolutional neural network for classification purposes and perform neuron screening in a target- driven manner to construct a feedback adjustment mechanism. Here, a simple example is given to clarify the feedback-modeling problem mentioned in this article. As shown in Figures 1(a) and 1(b), given an input image, the image has a simple face. Assuming that a convolutional neural network is trained to determine whether there is a human face in the image, the image is sent to the convolutional neural network. In the classification neurons at the highest level of the network, the neurons corresponding to the face category will be highly activated. /e neurons here are the target neurons in this paper, denoted as P.In this process, there are multiple paths between a pixel in the input image and the target neuron F. We abstract all of these pathways into a connecting pathway (CP), which is used to indicate that a pixel is connected to the target neuron. Typically, all pixels within the field of view of the target neuron will be connected to the target neuron. /is paper assumes that the target neuron field of view covers the full picture. Therefore, all the pixels and F in the figure have their own connection paths, as shown in Figure 1(c). Let P be the set of all these pathways. /e visual information of the face and the background in the image is transmitted to the target neuron F through P in a bottom-up manner. In this paper, R is used to indicate a rule for determining whether a connected path is connected to a target pixel and a target neuron. Then, the set P can be divided into two subsets, T and B, according to rule R. Therefore, the following questions are defined in this paper.

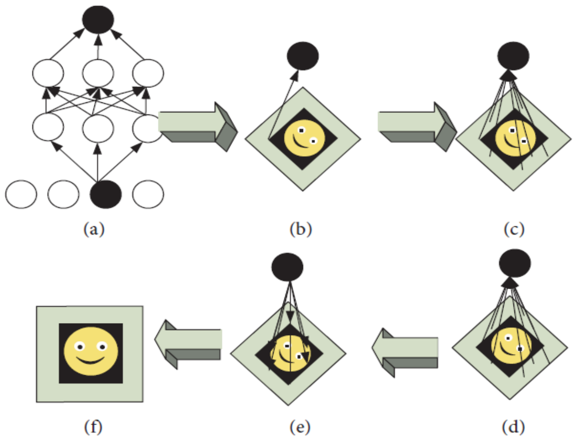

Fig 1(a) Modeling Definition

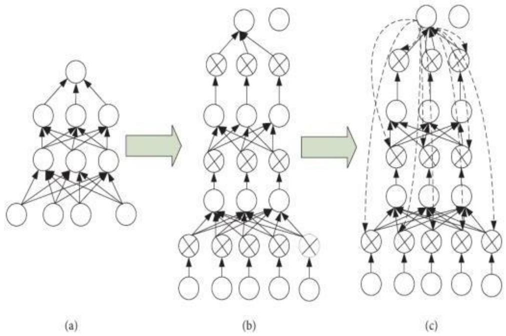

Fig 2. CNN Feedback network environment structure

Medical Image Segmentation Design. In this paper, a convolutional neural network with a feedback mechanism is constructed. First, fixed-size image block samples are extracted from the trained imageset that has been preprocessed. Feature learning isperformed through unlabeled image block samples,and the initial parameters of each layer of the network are trained. Then, further fine-tuning through the labeled image block samples is performedso that the convolutional neural network has a classification function. Then, the image block samplesto be segmented are classified, and the part of the content to be marked is added to the black and white binary image as the initial segmentation result. Finally, the results of threshold segmentation and morphological processing are used to optimize the results of accurate segmentation of certain medicalimages.

IV. EXPERIMENTAL ANALYSIS

The proposed method has been implemented on original medical images of CT-scan, MRI and X-ray. Fig. 4 shows the experimental results of proposed method by applying the 3x3 mask according to equation on the original images. It can be noted by visual observation, the overall image quality has been improved as well as the contrast of each image has been enhanced. In order to measure the resultant quality of enhanced images , three statistics metrics including: PSNR, MSE, and RMSE have been used. Table I presents the values of these metrics that performed for the enhanced medical images.

TABLE I. PSNR, MSE, AND RMSE VALUES FOR ENHANCED IMAGES USING THE CREATED EQUATION

	Image Quality Statistics		
	PSNR	*MSE*	*RMSE*
MRI	45.12	2.54	4.23
CT	33.78	2.41	15.14
x-ray	35.59	2.34	4.35

V. DISCUSSIONS AND CONCLUSION

The field of medical diagnostics and monitoring using medical images faces several technological, scientific and societal challenges. The technological advancements in imaging technologies have resulted in improved imaging accuracies. However, every modality of imaging has its own practical limitations, which is further imposed by the underlying nature of the organ and tissue structures. This enforces the need to explore the possibility to newer imaging technologies and to explore the possibility of using multiple imaging modalities. The ability of image fusion techniques to quantitatively and qualitatively improve the quality of imaging features makes multi-modal approaches efficient and accurate relative to unimodal approaches. The availability of a large number of techniques in feature processing, feature extraction and decision fusion makes the field of image fusion appealing to be used by medical imaging community. The methodological innovations specific to medical image fusion algorithms is rather limited at this stage, as majority of medical image fusion algorithms are derived from existing image fusion studies. The main challenge in applying image fusion algorithms is to ensure the medical relevance and aid for a better clinical outcome. The right combination of the imaging modalities, feature processing, feature extraction and decision fusion algorithms that targets a specific clinical problem in itself is a challenging and nontrivial task. Even the same images under consideration often require very different types of processing for different types of diagnostics over a region of interest. The major issues concerningfeature processing and extraction algorithms resultingfrom the presence of pixel intensity outliers, missing features, sensors errors, spatial inaccuracies, and inter-image variability remain an open problem inmedical image fusion. The inaccurate registration of the objects between the images is tightly linked to the poor performance of feature or decision level fusion on medical image fusion algorithms, and requires medical domain knowledge and algorithmic insightsto reduce the fusion inaccuracies.

Another, point of interest is that when addressing the medical image fusion problems, the emphasis has been in the direction of developing algorithms that try to improve the imaging quality and regions ofinterest within images. The need for improving the image quality arises from the signal noise and thephysical limitations of the imaging modality. The estimation of signal noise and compensation is considered as an important problem in medical imaging, and the advancements in enhancements to image quality can have a positive impact on the imagefusion process. Another area of interest is to improve the speed of processing especially in the cases of volumetric image fusion. An algorithmic approach is to develop algorithms that are optimized for high speed processing. However, they would be limited by the hardware and operating system capabilities. An alternate approach is to develop real-time processing systems in field programmable gate arrays and dedicate parallel computing graphical processing units. The speed is of primary importance in real-time image fusion during surgery or that involve continuous real-time monitoring. These are emerging areas of thoughts, and would require substantial progress in image fusion systems research.

The progress of this field largely depends on the trust that the medical practitioner and medical institutions place on the clinical improvements resulting from medical image fusion approaches. This is not an easy task, and would require a substantial convincing effort through technology improvements, access to the technological advancements and improving the usability of multi-modal systems in clinical setup. There are several technological advancements that can propel this growth. The primary growth comes from low-power high performance computing hardware developments for imaging that can process large volumes of high resolution images. In many medical imaging applications, although image resolutions are very high, the existing limitation in computing hardware makes the processing of suchimages in a time-limited clinical setup impossible. The advancements in parallel computing hardwaresuch as low cost graphical processing units can overcome much of the problems facing conventional algorithmic approaches. The development of low cost computing also depends on the advancements in the semiconductor technologies and how quickly the technologies can be transferred to the market. The development in cognitive computing algorithms and hardware is another major technological advancement that could have a significant impact in the way in which the images are processed and presented. The incorporation of natural learning techniques in imaging hardware and software would be the natural progression that would aim to compete with human judgment - which by far would be the most challenging aspect to adopt in the medical service industry, but an obvious technological advancement for progressing medical image fusion research.

In conclusion, image fusion techniques in terms of medical image modalities and organs of study have been discussed in this survey. The extensive developments in medical image fusion research summarized in this literature review indicate the importance of this research in improving the medical services such as diagnosis, monitoring and analysis. The availability and growth of a wide range of imaging modality has enabled progress in medical image fusion to be useful for clinical deployment. Although, there has been significant progress in the medical image fusion research, the application of the general fusion algorithms is limited by the practical clinical implications as imposed by the medicalexperts based on the requirements of specific medical studies. In addition to medical reasons, there exists technical challenges in image registration and fusion resulting from image noise, resolution difference between images, inter-image variability between the images, lack of sufficient number of images per modality, high cost of imaging and increased computational complexity with increasing image space and time resolution. Nonetheless, even under these challenging situations, the fused images provide the human observers improved viewing and interpretation of medical images. The algorithms usedfor medical image fusion studies have resulted in the improved imaging quality and have proved to be useful for clinical applications. The prominent approaches include wavelets transforms, neural networks, fuzzy logic, morphology methods, and classifiers such as support vector machines. Combining one or more image fusion methods is also observed to be successful in medical image analysis.

The algorithmic approaches to image fusion are also limited by the imaging hardware. The development of equipment that can perform multi-modal scanning is a challenging topic as it involves the risk of exposing the patients to additional radiation, longerexamination time, and increased cost of the device. This also involves having to look at compatibility issue of technologies as the space-time resolution and scanning speeds vary substantially from one imaging modality to another. The problem is much more significant in developing image fusion algorithms and devices for real-time medical applications such as robotic guided surgery. Since several of these challenges remain open and the image fusion in medical imaging has proved to be useful and the trust in these techniques is on the rise, it is expected that the innovation and practical advancements would continue to grow in the upcoming years.

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