AN AUTOMATIC MACHINE LEARNING BASED FRAMEWORK FOR 3D NEURITE IMAGE SEGMENTATION AND FAULT DETECTION

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ABSTRACT: Accurate reconstruction of anatomical connections between neurons in the brain using electron microscopy (EM) images is considered to be the gold standard for circuit mapping. A key step in obtaining the reconstruction is the ability to automatically segment neurons with a precision close to human-level performance. Despite the recent technical advances in EM image segmentation, most of them rely on hand-crafted features to some extent that are specific to the data, limiting their ability to generalize. Here, we propose a simple yet powerful technique for EM image segmentation that is trained end-to-end and does not rely on prior knowledge of the data. Our proposed residual deconvolutional network consists of two information pathways that capture full-resolution features and contextual information, respectively. We showed that the proposed model is very effective in achieving the conflicting goals in dense output prediction; namely preserving full-resolution predictions and including sufficient contextual information. We applied our method to the ongoing open challenge of 3D neurite segmentation in EM images. Our method achieved one of the top results on this open challenge. We thus expect our method to generalize well to other dense output prediction problems.

Proposed a simple yet powerful model known as residual deconvolutional network (RDN) to address this challage. Our proposed model naturally balances the tradeoff between increasing contextual window required for multi-scale reasoning and the ability to preserve pixel level resolution and accuracy expected for dense output prediction. We achieved these goals by adding multiple residual shortcut paths to a fully deep convolution network with minimum additional computations. this allows for the training of very deep deconvolutional that incorporate sufficient contextual information and the multi scale full resolutions features are extracted and provided through the residual paths. The final dense predicts are made by integrating features computed through both pathways, thereby achieving the conflicting goals in dense output prediction in the same framework.

KEYWORDS: EM Segmentation, RDN, neurite segmentation, deconvolutional Network

I. INTRODUCTION

The automated 3D reconstruction of neural in brain EM image stacks remains one of the most challenging problems in neuroscience. In such problems, neurons spanning multiple adjacent image slices are expected to be consistently identified and reconstructed. Conventionally, this problem has been approached as a 2D prediction task, where each image slice is segmented individually. Then, a post-processing step was performed to generate 3D segmentation. The post-processing step usually involves heuristic off-the-shelf classifiers that were trained to link similar segments together across the entire image stack. These classifiers usually rely on hand-crafted features which incorporate prior knowledge and understanding of the data. Thus, classifiers that worked well on some problems/ datasets are not guaranteed to perform similarly in different scenarios. It is thus desirable to design a fully trainable system with minimal post-processing to perform the 3D segmentation task in an end-to-end fashion. Currently, deep convolutional neural networks (CNNs) are one of the main tools used for semantic segmentation. These models are very powerful and capable of extracting hierarchical features from raw image data. They are characterized by their ability to learn features directly from the raw images without relying on prior knowledge. The functional model of Artificial Neural Networks (ANNs) is proposed to aid existing diagnosis methods. ANNs are currently a “hot” research area in medicine, particularly in the fields of radiology, cardiology, and oncology. In this attempt was made to make use of ANNs in the medical field. Hence a Computer Aided Diagnosis (CAD) system using ANNs to classify brain tumors was developed in order to detect and classify the presence of brain tumors according to Magnetic Resonance (MR) Image, and then determined which type of ANNs and activation function for ANNs is the best for image recognition. Also the study aimed to introduce a practical application study for brain tumor diagnosis.

Neural network must be able to determine the state of the brain according to MR image. In all procedures, image processing and ANNs design, MATLAB was included. From each MR Image a Harlick texture features was extracted to prepare training data which was introduced to neural network as input and target vectors. ANNs was designed using MATLAB tool.Conventional statistical methods can be used to model nonlinear relationships, but they require complex and extensive mathematical modeling. Neural networks provide a comparatively easier way to do the same type of analysis. Well design and training of Neural Network make it qualified for decision making operations when it faced with new data outside training data; this will provide ANNs with high reliability exactly like an expert person. There are two problems that face ANNs designers in any application comprising of generalization.

i) network structure
ii) network

In designing ANNs, a suitable architecture for the specific application must be well chosen; this involves: a. Choosing a suitable network type for application,

i) Number of layers,
ii) Number of nodes in hidden layers, and
iii) Activation functions between layers.

Network Generalization means how much the neural network is able to work with different data. Designers of ANN are always faced by the extend of network generalization, i.e. despite a well designing and training of ANN that decreases the performance error to the least value; ANN fails when fed with a new input data and gives worst performance. Many studies were carried out using artificial neural networks for brain tumor detection and recognition

II. RELATED WORKS

Deeper neural networks are more difficult to train. We present a residual learning framework to ease the training of networks that are substantially deeper than those used previously. We explicitly reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. We provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the Image Net dataset we evaluate residual nets with a depth of up to 152 layers but still having lower complexity. An ensemble of these residual nets achieves 3.57% error on the Image Net test set. This result won the 1st place on the ILSVRC 2015 classification task. When deeper networks are able to start converging, a degradation problem has been exposed: with the network depth increasing, accuracy gets saturated (which might be unsurprising) and then degrades rapidly. Unexpectedly, such degradation is not caused by over fitting, and adding more layers to a suitably deep model leads to higher trainingerror, as reported in and thoroughly verified by our experiments.

Convolutional networks are powerful visual models that yield hierarchies of features. We show that convolutional networks by themselves, trained end-to-end, pixelsto- pixels, exceed the state-of-the-art in semantic segmentation. Our key insight is to build "fully convolutional" networks that take input of arbitrary size and produce correspondingly-sized output with efficient inference and learning. Fully convolutional networks To our knowledge, the idea of extending a convnet to arbitrary-sized inputs first appeared in Matan, which extended the classic Le Net to recognize strings of digits. Because their net was limited to one-dimensional input strings, Matanet al. used Viterbi decoding to obtain their outputs. Wolf and Platt expand convnet outputs to 2-dimensional maps of detection scores for the four corners of postal address blocks. Both of these historical works do inference and learning fully convolutionally for detection. Ning define a convnet for coarse multiclass segmentation of C. Elegans tissues with fully convolutional inference. (Jonathan Long∗Evan Shelhamer∗Trevor Darrell UC Berkeley 2015). A novel semantic segmentation algorithm by learning a deep deconvolution network. We learn the network on top of the convolutional layers adopted from VGG 16-layer net. The deconvolution network is composed of deconvolution and unpooling layers, which identify pixel wise class labels and predict segmentation masks. We apply the trained network to each proposal in an input image, and construct the final semantic segmentation map by combining the results from all proposals in a simple manner. The proposed algorithm mitigates the limitations of the existing methods based on fully convolutional networks by integrating deep deconvolution network and proposal-wise prediction; our segmentation method typically identifies detailedstructures and handles objects in multiple scales naturally. Present a novel method that utilizes a hierarchical structure and boundary classification for 2D neuron segmentation.

With a membrane detection probability map, a watershed merge tree is built for the representation of hierarchical region merging from the watershed algorithm. A boundary classifier is learned with non-local image features to predict each potential merge in the tree, upon which merge decisions are made with consistency constraints to acquire the final segmentation. Independent of classifiers and decision strategies, our approach proposes a general framework for efficient hierarchical segmentation with statistical learning. We demonstrate that our method leads to a substantial improvement in segmentation accuracy. Scene labeling consists in labeling each pixel in an image with the category of the object it belongs to. We propose a method that uses a multi scale convolutional network trained from raw pixels to extract dense feature vectors that encode regions of multiple sizes centered on each pixel. The method alleviates the need for engineered features, and produces a powerful representation that captures texture, shape and contextual information. We report results using multiple post-processing methods to produce the final labeling. Among those, we propose a technique to automatically retrieve, from a pool of segmentation components, an optimal set of components that best explain the scene; these components are arbitrary, e.g. they can be taken from a segmentation tree, or from any family of over-segmentations.

III. PROPOSED METHODOLOGY

Our proposed model naturally balances the tradeoff between increasing contextual window required for multi-scale reasoning and the ability to preserve pixel level resolution and accuracy expected for dense output prediction. We achieved these goals by adding multiple residual shortcut paths to a fully deconvolutional network with minimum additional computations. This allows for the training of very deep deconvolutional networks that incorporate sufficient contextual information, and the multi scale full-resolution features are extracted and provided through the residual paths. The final dense predictions are made by integrating features computed through both pathways, thereby achieving the conflicting goals in dense output prediction in the same framework. We evaluated our method on the challenging problem of neurite segmentation from 3D EM images, which is a key step in dense brain circuit reconstruction.

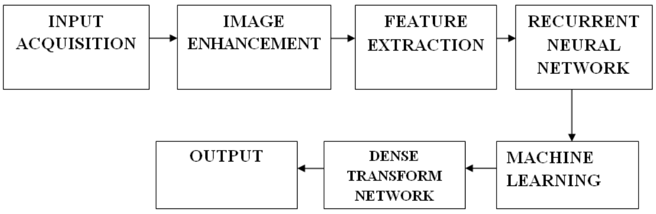
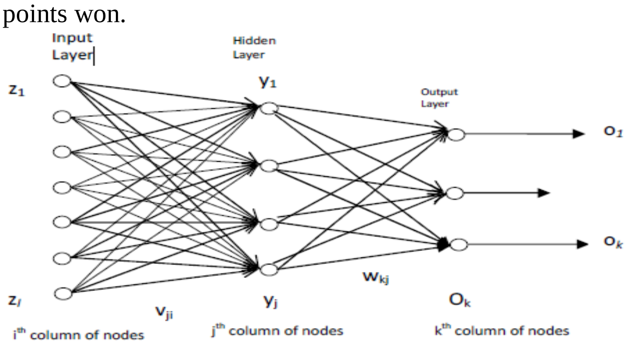


IMAGE ACQUISITION
Image acquisition in image processing can be broadly defined as the action of retrieving an image from some source, usually a hardware-based source, so it can be passed through whatever processes need to occur afterward. Performing image acquisition in image processing is always the first step in the workflow sequence because, without an image, no processing is possible. The image that is acquired is completely unprocessed and is the result of whatever hardware was used to generate it, which can be very important in some fields to have a consistent baseline from which to work. One of the ultimate goals of this process is to have a source of input that operates within such controlled and measured guidelines that the same image can, if necessary, be nearly perfectly reproduced under the same conditions so anomalous factors are easier to locate and eliminate.

IMAGE ENHANCEMENT
Enhancement is the modification of an image to alter impact on the viewer. Generally enhancement distorts the original digital values; therefore enhancement is not done until the restoration processes are completed. Digital image processing plays a vital role in the analysis and interpretation of remotely sensed data. Especially data obtained from Satellite Remote Sensing, which is in the digital form, can best be utilized with the help of digital image processing. Image enhancement and information extraction are two important components of digital image processing. Image enhancement techniques help in improving the visibility of any portion or feature of the image suppressing the information in other portions or features. Information extraction techniques help in obtaining the statistical information about any particular feature or portion of the image. These techniques are discussed in detail and illustrated in this article.

RECURRENT NEURAL NETWORK
Google's speech recognition reportedly experienced a dramatic performance jump of 49% through CTC-trained LSTM, which was used by Google voice search. LSTM broke records for improved machine translation, Language Modeling and Multilingual Language Processing. LSTM combined with convolutional neural networks(CNNs) improved automatic image captioning.

FULLY RECURRENT
Basic RNNs are a network of neuron-like nodes, each with a directed (one-way) connection to every other node. Each node (neuron) has a time-varying real-valued activation. Each connection (synapse) has a modifiable real-valued weight. Nodes are either input nodes (receiving data from outside the network), output nodes (yielding results), or hidden nodes (that modify the data en route from input to output). For supervised learning in discrete time settings, sequences of real-valued input vectors arrive at the input nodes, one vector at a time. At any given time step, each non-input unit computes its current activation (result) as a nonlinear function of the weighted sum of the activations of all units that connect to it. Supervisor-given target activations can be supplied for some output units at certain time steps. For example, if the input sequence is a speech signal corresponding to a spoken digit, the final target output at the end of the sequence may be a label classifying the digit. In reinforcement learning settings, no teacher provides target signals. Instead a fitness function or reward function is occasionally used to evaluate the RNN's performance, which influences its input stream through output units connected to actuators that affect the environment. This might be used to play a game in which progress is measured with the number of points won.



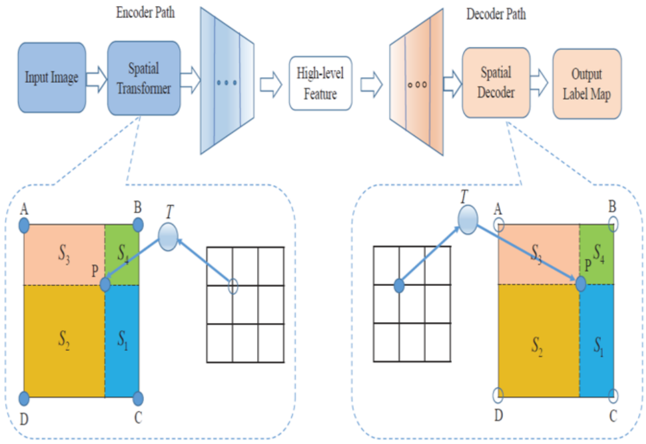
Each sequence produces an error as the sum of the deviations of all target signals from the corresponding activations computed by the network. For a training set of numerous sequences, the total error is the sum of the errors of all individual sequences.

MACHINE LEARNING
This project investigates the use of machine learning for image analysis an pattern recognition. Examples are shown using such a system in image content analysis and in making diagnoses and prognoses in the field of healthcare. Given a data set of images with known classifications, a system can predict the classification of new images. As an example, in the field of healthcare, given a data set of fine needle aspirate (FNA) images of breast masses that are each classified as benign or malignant, a new FNA of a breast mass can be classified as benign or malignant.
There are at least two parts to any such system. The first part is an algorithm for creating a feature vector (also known as a data point) given an image. A feature vector consists of several numbers that are measured or calculated from the image. These features are then used by the second part of the system, a machine learning algorithm, to classify unknown feature vectors given a large database of feature vectors whose classifications are known.
These two parts of such a system are not entirely independent – that is the design of the machine learning algorithm may benefit by knowing how the features are extracted from the image, and the feature extracting may be

more successful if the type of machine learning algorithm to be used is known. However, in order to limit the scope of this project, only the second part of such a system is explored. That is, this project focuses on developing a system that uses machine learning to classify unknown images given a database of images and classifications, all of which have already been broken down into feature vectors by an image processing algorithm.

DENSE TRANSFORM NETWORK

A current deep learning method for dense prediction is to apply a model on a regular patch centered on each pixel to make pixel-wise predictions. These methods are limited in the sense that the patches are determined by network architecture instead of learned from data. In this work, the dense transformer networks, this can learn the shapes and sizes of patches from data. The dense transformer networks employ an encoder-decoder architecture, and a pair of dense transformer modules are inserted into each of the encoder and decoder paths. The novelty of this work is that we provide technical solutions for learning the shapes and sizes of patches from data and efficiently restoring the spatial correspondence required for dense prediction. The proposed dense transformer modules are differentiable, thus the entire network can be trained. The proposed networks on natural and biological image segmentation tasks and show superior performance are achieved.A pair of dense transform modules is inserted into each of the encoder and decoder paths. In the spatial module, values at points A, B, C, and D are given from the previous layer, and we need to estimate value for point P. In contrast, in the decoder layer, value at point P is given from the previous layer, and we need to estimate values for points A, B, C, and D.



AN ENCODER-DECODER ARCHITECTURE

The Encoder-Decoder LSTM is a recurrent neural network designed to address sequence to sequence problems. Sequence to sequence prediction problems are challenging because the number of items in the input and output may vary. Sequence prediction involves in forecasting the next value in a real valued sequence. This is framed as a sequence of one input time step to one output time step or multiple input time step to one output time step sequence prediction problem.

DECODER SAMPLER

In the decoder sampler, need to estimate values of regular grid points based on those from arbitrary decimal points, i.e., those that do not lie on the regular grid. After the TPS transformation, it may be mapped to an arbitrary point. Therefore, the values of grid points A, B, C, and D need to be computed based on values from a set of arbitrary points.

IV. RESULTS AND DISCUSSIONS

In this, the proposed model is very effective. Achieving the conflicting goals in dense output prediction. Full-resolution predictions and including sufficient contextual information.

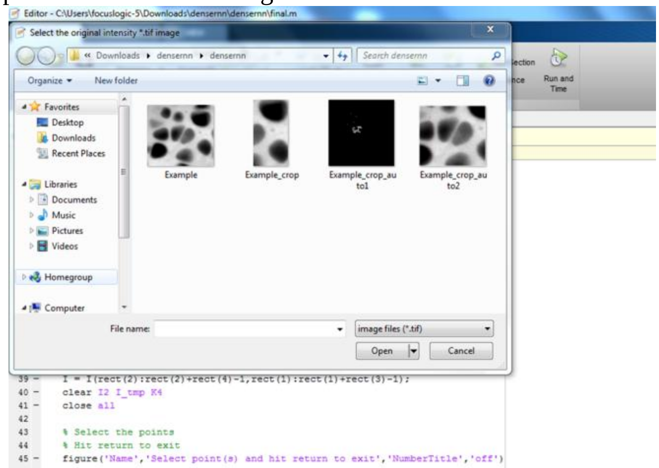


Figure shows the RAW image of Electron Microscopy image Segmentation with size of 306X285.

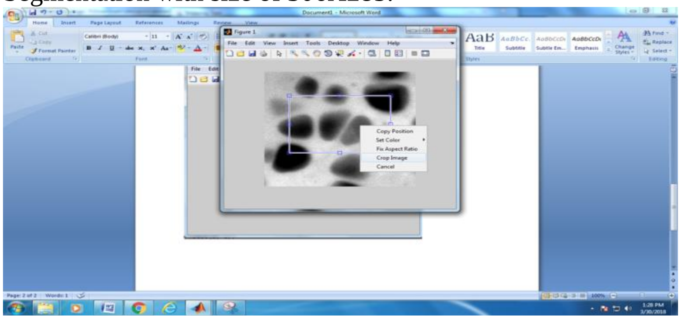


Figure Shows the Encoder sample of image. This is used to select a particular region of interest for nuclei detection. The Encoder to perform non-linear up sampling of their input feature maps. The architecture of the encoder network is topologically identical to the 13 convolutional layers.

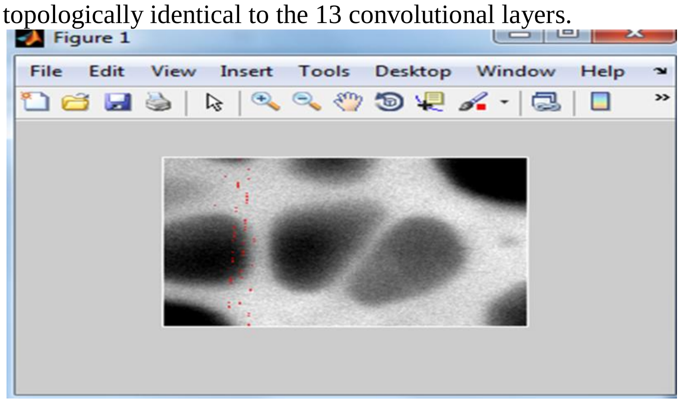


Figure shows neuron Segmentation in EM Image. The effectiveness of contextual information for accurate segmentation. Segmentation generated by recurrent neural network for the effect of resolution-preserving paths on the final segmentation.

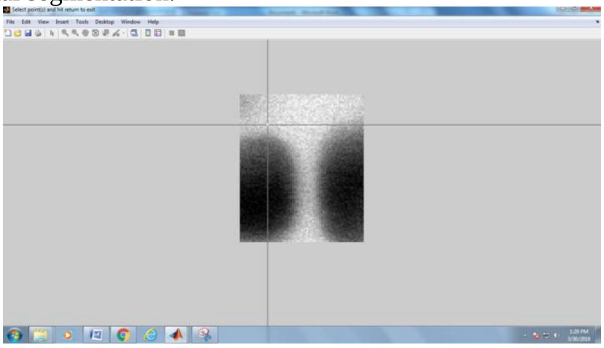


Figure shows the decoded architecture of the image. Image enhancement is the process of adjusting digital images so that the results are more suitable for display or further image analysis This is used to select the four arbitrary points in particular region of interest.

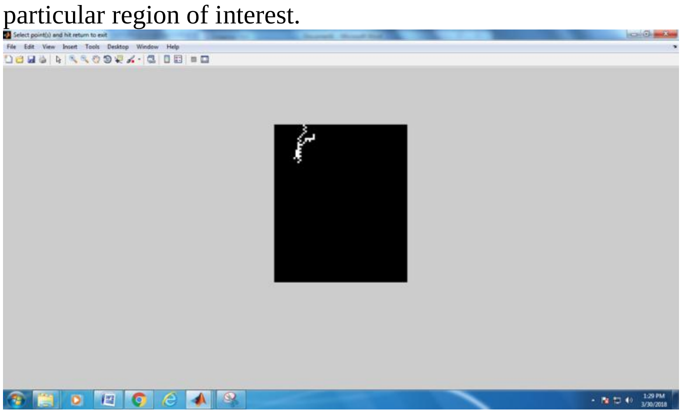


Figure Shows the output image. The accurate nuclei segmentation may contribute to development of successful system which automate the analysis of microscope images for pathology detection It shows the nuclei segmentation fault.

V. CONCLUSION

Recurrent neural networks and deep learning approaches sensitive to the local neighborhood for nuclei detection and classification in routine stained histological images from image net. Deep learning approach that enables automated learning of feature sets instead of handcraft features. The proposed model with image net is trained then tested on nuclei cell tumour without retrain thus leading itself to be useful tool for better understanding of tumor microenvironment.

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