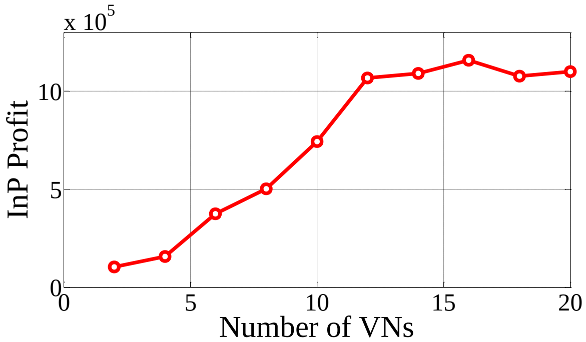

Figure 2 – InP profit

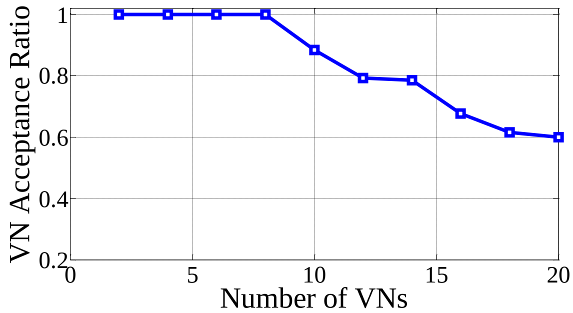

Figure 3 – VN acceptance ratio

5. Conclusion

In this paper, we formulate the VNE problem in FiWi access network to be an ILP where more comprehensive constraints are taken into account to achieve the optimal solution. Future works will highlight the network performance improvement including Quality of Service (QoS) satisfying, energy-saving and survivability guaranteeing.

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УДК 004

COMPUTER-AIDED DIAGNOSIS FOR PATHOLOGY IMAGE

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Abstract. *Accurate analysis for pathology image is of great importance in medical diagnosis and treatment. Specifically, nucleus detection is considered as an important prerequisite for this purpose. With the rapid development of computer-aided diagnosis, several computer-aided diagnosis (CAD) models using machine learning and deep learning have been developed fo accurate automatic nucleus detection. In this paper, we propose a nucleus detection method using two layers' sparse autoencoder (SAE) and transfer learning. First, 26832 image patches of breast cancer are utilized to train the SAE in an unsupervised learning method, which could be regarded as the feature extraction process. Then, the softmax classifier are used to classify that whether an image patch contains a complete nucleus or not. Finally, following transfer learning and sliding window techniques, we use the trained SAE and softmax models for nucleus detection on liver cancer pathology image. Experiments demonstrate that our proposed method could achieve the satisfactory detection results.*

1. Introduction

Diagnosis from pathological images remains the "gold standard" in diagnosing a number of diseases including most cancers 1. Nucleus detection is a critical step and it provides location information of each cell nuclei for further treatment. The automated detection method has become a research focus due to the fact that manual detection is time-consuming and operator subjective.

Recently, computerized nucleus detection approaches have been developed over the years with the aim to provide efficient image interpretation automatically. For example, Wang *et al*. 2

used a cascaded classifier which uses a combination of hand-crafted features and features learned through CNN to detect mitotic cells. Xie *et al*. 3 recently presented structural regression CNN capable of learning a proximity map of cell nuclei and was shown by the authors to provide more accurate detection results. Finally, Sirinukunwattana *et al*. 4 proposed a Spatially Constrained Convolutional Neural Network (SC-CNN) to perform nucleus detection. SC-CNN regressed the likelihood of a pixel being the center of a nucleus, where high probability values were spatially constrained to locate in the vicinity of the center of nuclei.

In conclusion, "deep learning" strategies have been widely applied for pathology image detection successfully. In this paper, we employ stacked sparse autoencoder (SSAE) and transfer learning technologies for detecting nuclei on liver cancer pathology images. The remainder of the paper is organized as follows. Section 3 briefly introduces the detection methods and Section 4 shows our experiment results.

2. Methods

The stacked autoencoder is a neural network consisting of multiple layers of basic SAE (see Fig. 1) in which the outputs of each layer are wired to the inputs of each successive layer. In this paper, we consider the two layer's SAE, which consists of two hidden layers, and the stacked sparse autoencoder (SSAE) to represent the two layer SAE. The architecture of SSAE is shown in Fig. 2.

Similar to SAE, training an SSAE involves finding the optimal parameters simultaneously by minimizing the discrepancy between input and its reconstruction. After the optimal parameters are obtained, the SSAE yields a function that transforms input pixel intensities of an image patch to a new feature representation of nuclear structures.

As Fig. 2 shows, with SSAE, each training patch of pixel intensities is represented by a high-level structured representation of nuclei or non-nuclei patches in the second hidden layer of the model. For the two class classification problem considered in this paper, the label of the patch is 1 or 0, where 1 and 0 refer to the nuclear and non-nuclear patches, respectively. Note that in the SSAE learning procedure, the label information is not used. Therefore, SSAE learning is an unsupervised learning scheme. Finally, the learned high-level representations of nuclear structures are utilized to train the softmax classifier.

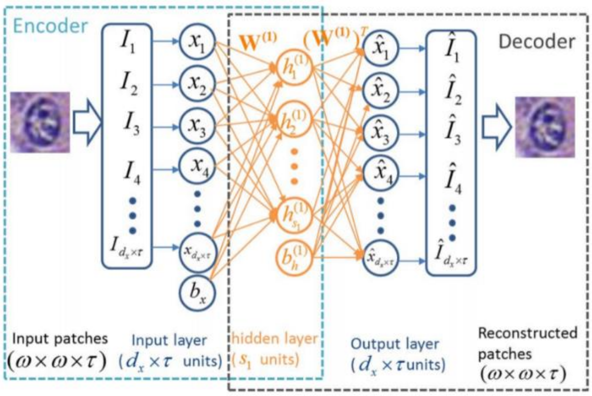

Figure 1 – The architecture of basic autoencoder

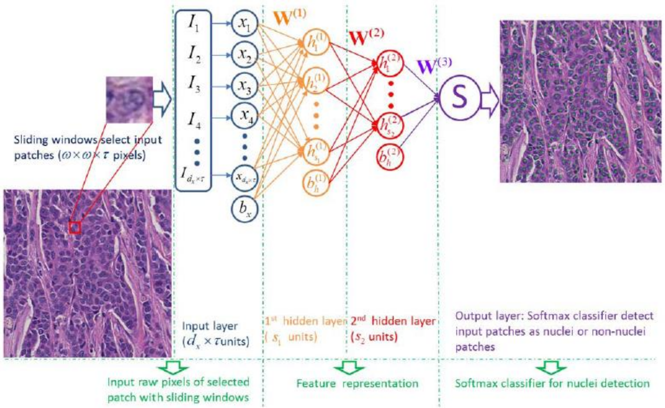

Figure 2 – The flowchart of SSAE

3. Experiment Results

Our experiments employ image patches of breast cancer from the open dataset to train the SSAE and the softmax classifier. However, our intention of this paper is for nucleus detection on liver cancer pathology images. To address this issue, we use the transfer learning and sliding window techniques to accurate detect all nuclei. An example illustrating our method on the liver cancer pathology image is shown in Fig. 3. Left is an original image and right is the detection result, the green points represent the center of all nuclei. Obviously, most nuclei could be marked accurately.

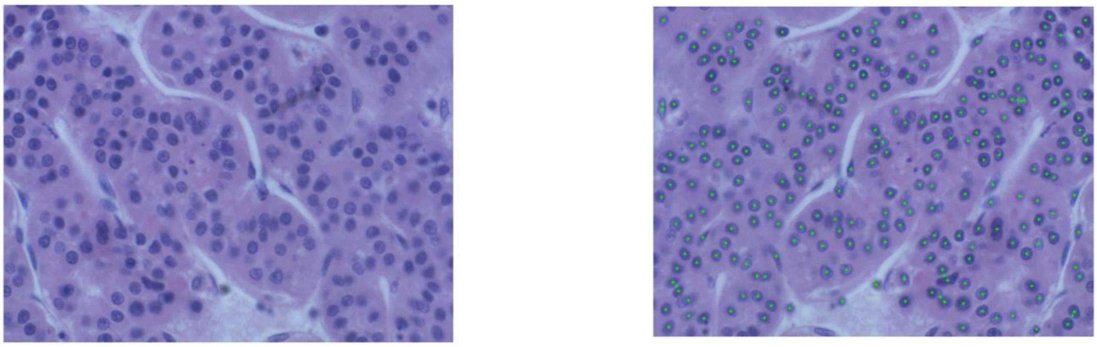

Figure 3 – Detection results on the liver cancer pathology image. Left: original image. Right: detection result

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УДК 004

EXPERIMENTAL INVESTIGATION ON LOW SPEED WIRE ELECTRICAL DISCHARGE TURNING AND ITS APPLICATION IN FABRICATING MICRO PARTS

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Abstract. *This paper firstly proposed the method of the low speed wire electrical discharge turning (LS-WEDT) method to fabricate micro parts. Firstly, the rotating apparatus submerged in working fluid is designed and manufactured to enable the low speed wire electrical discharge machine to generate cylindrical geometries. Besides, material removal rate, surface roughness and machining precision of micro shafts manufactured by the LS-WEDT are respectively investigated. Experimental results display that the micro-rod of 70μm in diameter and 1000μm in length can be successfully fabricated with high machining precision and good surface quality of the micro shaft.*

1. Introduction

Wire electrical discharge machining (WEDM) is a thermoelectric process which can remove material by a series of electrical sparks generated between the workpiece and tool electrode [1]. The non-contact and negligible cutting force of the EDM process make it have the unique superiority in fabricating micro parts and components. With micromechanics and micro-electro-mechanical system have come to a practical period, the demand for micro parts and components with the diameter range of 10μm and 1mm is significantly increased, such as micro gear shafts, mechanical and electrical contact probes, instrument probes, micro-ejector pins and micro-tools.

Zhao *et al*. [7] used the block electrode discharge grinding method to fabricate micro rods at a high machining speed, but the dimensional accuracy is poor because of the block electrode wear.