A Novel Modified Deep Belief Network for Gastric Cancer Prediction

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Abstract:
Gastric cancer, one of the most fatal cancers in the world is characterized by a growth of cancerous cells within the lining of the stomach. A novel method is proposed for accurate segmentation and classification of gastric cancer. The pathological images are acquired from the Pathology Outline in which the images are divided into three classes namely Adenocarcinoma, GIST and Neuroendocrine-Carcinoid. The image pre-processing step primarily focuses on image re-sizing, noise removal and image enhancement. The processing stage includes image segmentation. The two main approaches used for image segmentation are thresholding and edge detection. The feature extraction step consists of the binarization and masking approach. The masking approach is used for red-spot detection. The feature vectors extracted are normalized to get a uniform value in intensity. In order to achieve an efficient feature set, the extracted original set of features is processed and pre-trained by Deep Boltzmann Machine (DBM). Before feeding the KNN classifier with the selected features, the pre-trained images are divided into two sets, training set (70%) and testing set (30%). Therefore, the KNN classifier is trained by using the training set to predict and classify the type of cancer.

I. INTRODUCTION
Gastric (Stomach) cancer usually sets about in the mucus-producing cells that line the stomach. This type of cancer is called adenocarcinoma. In 2018, gastric cancer is responsible for 1,000,000 new cases and an estimated 783,000 deaths. This quantitative analysis makes it the fifth most frequently diagnosed cancer and the third leading cause of cancer death [1]. However, cancer in the area where the top part of the stomach (cardia) touches the lower end of the swallowing tube (oesophagus) has become frequent. This portion of the stomach is called the gastroesophageal junction. Cancer begins when a mutation occurs in a cell's DNA. This mutation makes the cells to grow and divide at a rapid rate. The accumulating cancerous cells constitute a tumour that can seize nearby structures. The cancer cells get detached from the tumour to spread throughout the body. The dominant risk factors for gastroesophageal junction cancer are past records of gastrointestinal reflux disease (GERD) and obesity. The gastric cancer is broadly classified into three types: Adenocarcinoma, GIST and Neuro-Endocrine Carcinoid. Its symptoms are ambiguous, which leads to late diagnoses, reducing the patients' chances of survival [6]. This fact makes gastric cancer difficult to treat. Manual pathological inspection of gastric slices is time-consuming and usually suffers from inter-observer variations [4]. Due to high image resolution, the diagnosis of gastric cancer is very hard and time consuming [1]. Technically, the segmentation problem suffers from various sizes, vague boundaries, and the non-rigid characters of cancerous regions [7]. A novel method is proposed for accurate segmentation and classification of gastric cancer.

A. Related work
In cancer studies, the prediction of cancer outcome based on a set of prognostic variables has been a long-standing topic of interest. Artificial neural network (ANN) models are primarily useful in prediction when nonlinear approaches are required to sift through the plethora of available information [2]. Five separate single time-point ANN models were developed to predict the outcome of patients after 1, 2, 3, 4, and 5 years. The performance of ANN models in predicting the probabilities of death is consistently high for all time points according to the accuracy [2]. To improve the cancer tissue classification performance, slide-level weak label is exploited for training the model with patches without region-level label [3]. A deep learning based framework namely GastricNet is used for automatic gastric cancer identification. The proposed network adopts different architectures for shallow and deep layers for better feature extraction [4]. Mask R-CNN is the latest method in the related field at the beginning of the research. The Mask R-CNN method is used to detect the pathological sections of gastric cancer and segment the cancer nest, and then optimize it by adjusting parameters [5]. Automatic gastric cancer segmentation is a challenging problem in digital pathology image analysis. For addressing the challenges, a deep learning based method is used and several customized modules are integrated. Structurally, the basic form of convolution is replaced with deformable and Atrous convolutions in specific layers, for adapting to the non-rigid characters and larger receptive field [7].

B. Dataset
The pathological images used in this paper are derived from the Pathology outline database. Pathology Outline is a free educational resource with high quality pathology images of benign and malignant neoplasms and related entities. The dataset has been delicately annotated by medical specialists twice per pathological image. The images have been cropped from the whole pathological slides of gastric area, with typical cancerous regions. Each image is accompanied by a comment on pertinent clinical and pathological features. About 100 pathological images of gastric cancer have been acquired for training the neural network. In the project, the dataset is randomly divided into a training set (70%) and a testing set (30%). The training set is used to train the model parameters and the testing set is used.
to verify the effect of model. Before feeding the images into the network, the images are resized and cropped. Basic image augmentation procedures are performed before training the neural network.

Figure.1. Three image label samples obtained from the gastric cancer segmentation dataset.

II. METHODS

There are four important stages in a gastric cancer prediction and classification system. These include image pre-processing, segmentation, feature extraction and normalization, the deep belief network and classifier construction. Fig.2 shows the proposed method for the prediction and classification of the three types of gastric cancer.

A. Pre-processing: Image pre-processing that primarily focuses on image re-sizing, noise removal and image enhancement. Median filters are used for de-noising and log transformation techniques are used for image enhancement.

Image-re-sizing. The acquired RGB images are resized to 100 x 100 pixel images. In short, resizing is a geometric transformation and more precisely a scale transformation. After image resizing, the RGB image is converted to a gray scale image. As colour increases the complexity of the model, RGB to gray conversion is usually done because the inherent complexity of gray level images is lower than that of colour images.

Noise-removal. The second step of pre-processing is the usage of median filters. Median filtering is a common non-linear method for noise suppression that has unique characteristics. Median filtration on a noisy digital image is a dramatic reduction in impulse noise.

Image enhancement. The image enhancement is done with gray-scale transformations such as logarithmic transformation. During log transformation, the dark pixels in an image are expanded. Therefore, the higher pixel values are kind of compressed in log transformation.

Figure.2. The proposed Gastric Cancer prediction and classification system

Figure.3. Pre-processing output.
B. Image Segmentation

The processing stage primarily includes image segmentation. The two main approaches used for image segmentation are thresholding and edge detection.

**Thresholding.** Image thresholding is an effective way of dividing an image into a foreground and background. The global thresholding searches for a threshold that minimizes the intra-class variances of the segmented image and achieves better results when the histogram of the original image has two distinct peaks, one belongs to the foreground while the other belongs to the background.

**Canny edge detection.** An efficient method of edge detection is the canny edge detection. It results in significantly reduced memory requirements, decreased latency and increased throughput with no loss in edge detection performance. It is considered the most optimal method of finding edges with good detection, good localization and single response to an edge. Edge detection refers to the process of identifying and locating sharp discontinuities in an image.

C. Feature Extraction

The image feature extraction step uses techniques and algorithms to detect and isolate the desired features of an image. The feature extraction step consists of the morphological feature extraction, binarization and masking approach.

**Morphological features extraction.** Morphological techniques probe an image with a small shape or template called a structuring element. The structuring element is positioned and placed at all possible locations in the image and it is compared with the corresponding neighbourhood of pixels. Image dilation and erosion are the basic operators in the area of mathematical morphology.

**The binarization approach.** The binarization approach is based on the fact that the number of black pixels is much greater than white pixels in normal cancer images. Therefore, the sum of black pixels is computed for normal and abnormal images to obtain an average which is used as a threshold. If the count of black pixels is greater than the threshold for a given image, then it is considered abnormal.

**Masking for red-spot detection.** Red-spot detection is one of the important feature extraction steps. Masking approach depends on the fact that the masses appear as red linked areas inside Region Of Interest (ROI), as they increase the probability of cancer presence. The appearance of solid red mass indicates the presence of cancer. The masked image indicates the presence of a red-spot in the image. The extracted features are finally normalized. The purpose of normalization is to calibrate the different image pixel intensities into a normal distribution. This improves the appearance of the image making it look better for the visualizer.
D. MODIFIED DEEP BELIEF NETWORK AND CLASSIFIER

To achieve an efficient and effective feature set, the extracted set of original features is processed and pre-trained by a deep learning algorithm called the Deep Boltzmann machine.

a. Deep Boltzmann Machine. A Deep Boltzmann Machine (DBM) is an organization of equally joined stochastic two fold neuron units. It comprises a prearrangement of visible neuron units. DBM can be arranged as a bipartite graph with odd layers on one side and even layers on one side. The units located within the layers are independent of each other. However, they are dependent on neighbouring layers. Learning is made efficient layer by layer pre training - Greedy layer wise pre training slightly different than done in DBM. After learning the binary features in each layer, DBM is fine-tuned by back propagation. It is unsupervised, probabilistic, generative, graphical models consisting of stacked layers of Restricted Boltzmann Machine (RBM). It is used to identify latent features present in the data. The input features are pre-trained through piling a stack of DBM’s with unsupervised greedy algorithm by haphazardly setting the feature values to the neuron unit u of the visible layer. The pre-trained attribute values of DBM are used as the feedback information for training the subsequent DBM’s in the pile. The DBM is fine-tuned by calculating the misclassification error derivatives. The Root Mean Square Error (RMSE) is calculated as:

\[ \text{RMSE} = \sqrt{\text{mse}(I-\text{visible}_p)} \]

Where \( \sqrt{\text{mse}} \) is square root, \( \text{mse} \) is mean squared error, I is the input image and \( \text{visible}_p \) is the visible units obtained by sampling the hidden units. The steps for implementation are:

Initialization. The input image is converted into binary units. The input weights \( W \) are randomly generated using the number of neurons and also the initial bias for the visible layer and hidden layer are calculated.

Training Process. The error history is initialized for every pixel iteration in the input sample. The Gibbs sampling energy function is activated. The hidden and visible units are found by sampling the hidden and visible layer respectively using the sigmoid function and converted into binary form.

Updation. This step involves the calculation of positive and negative divergence. The weights are updated using the contrastive divergence, which is calculated using the positive and negative divergence. The bias of the visible and the hidden layer are updated and RMSE is computed.

Training Accuracy. With the help of the updated biases of the visible and the hidden layer, the training accuracy is calculated without the non-binary units.

\[ \text{Accuracy} \, (\%) = \sqrt{\text{mse}(I2-\text{Tr}_V)} \times 100 \]

where \( I2 \) is the input sample without conversion to binary units, \( \text{Tr}_V \) is the sigmoid function calculated using the updated biases of the visible layer.

b. KNN Classifier. In this final stage, the pre-trained features are used by the KNN (K Nearest Neighbour) classifier for classifying the cancer into three classes namely Adenocarcinoma (class 1), GIST (class 2), Neuroendocrine Carcinoid (class 3). Before feeding the KNN classifier with the selected features, the pre-trained cancer images are divided into two sets, training set (70%) and testing set (30%). Consequently, the KNN classifier is trained by the training set to classify the cancer. KNN classifier is a supervised classification scheme. A subset of the entire dataset (training set) for which the user specifies the class assignments, is used as an input to classify the remaining members of the dataset. The training set can be validated by leaving out each element of the training set and using the remaining elements of the training set to classify the one left out.
III. CONCLUSION

To address the challenges in automatic gastric cancer segmentation in digital pathology image analysis, we have proposed a Modified Deep Belief Network with a classifier and achieved an accuracy of 94.85%. The quantitative comparisons against several prior methods demonstrate the superiority of our approach. Concurrently, more studies and research needs to be done on datasets and develop algorithms. This would help in promoting the fusion of deep learning technology and pathological diagnoses.

IV. REFERENCES


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Figure.9. Accuracy