Polyp Classification and Clustering from Endoscopic Images Using Competitive and Convolutional Neural Networks

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Abstract

Understanding the type of Polyp present in the body plays an important role in medical diagnosis.

CNN and Self Organizing Maps are used to classify and cluster from Endoscopic Images . Using Competitive Neural Network different polyps available from previous data are plotted with the new polyp according to their structural similarity.

Such kind of presentation not only help the doctor in its easy understanding but also helps him to know what kind of medical procedures were followed in similar cases.

Introduction

This paper proposes two methods to classify and cluster the Endoscopic polyp images.

One method is using **Self organizing map**. This method uses principles of competitive learning. It works by increasing the specialization of each node in the network. In contrast to other standard Neural networks, it only has input and output layers.

The second method involves use of **CNN**. A new CNN model was generated to classify Stain Narrow Band Endoscopic images into Benign and Malignant classes.

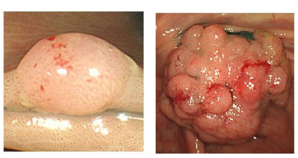

Figure1: Benign and Malignant Polyp

Convolutional Neural Network

A Convolutional Neural Network (CNN) is comprised of one or more convolutional layers (often with a subsampling step) and then followed by one or more fully connected layers as in a standard multilayer neural network.

A self designed and trained layer structure as shown below was used to classify Benign and Malignant polyps. Input images were processed using smoothing filters and edges were detected.
This network was trained using 500 images of both kinds. K-fold cross validation was used on this set.

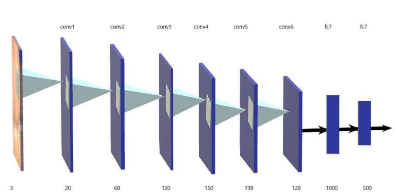

Figure2: Designed Neural Net Structure

Self Organizing Maps

The SOM algorithm is based on competitive learning. Points that are near each other in the input space are mapped to nearby map units in the SOM.

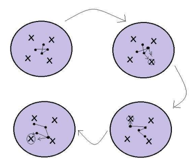

Figure3: Forming of a map

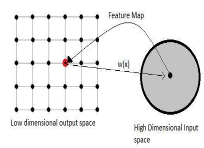

Figure4: Working of SOM

For finding the Best matching unit, we iterate through all the nodes and compare the Euclidean distance between every node's weight vector and present input vector.

$$dist^2 = \sum_{i=0}^{n} (V - W)^2$$

Where V is current input vector and W is node's weight vector.

After selecting the BMU Number of nodes coming in a BMU's neighbourhood depends on the radius of neighbourhood chosen. This area of neighbourhood will keep on shrinking with every iteration.

$$\sigma(t) = \sigma_o e^{-t/\lambda}$$

Where σ_o denotes the width of the lattice at time t=0, λ denotes the time constant

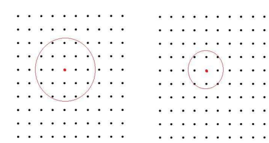

Figure5: Shrinking of radius

This radius will keep shrinking until only one neuron that is the BMU is present inside the neighbour.
Weight vector of every node present inside the current neighbourhood is updated using

$$W(t+1) = W(t) + \Theta(t)L(t)(V(t) - W(t))$$

L is the learning rate which decays with time using

$$L(t) = L_o e^{-t/\lambda}$$

Now practical use suggests that not only the Learning rate should decay with iteration but also it's effect should decrease as the distance from the best matching unit increase. For That we use Gaussian Decay function.

$$\Theta(t) = e^{-dist^2/2\sigma(t)^2}$$

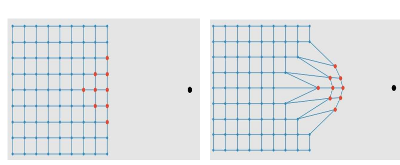

Figure6: Feature map before and after training

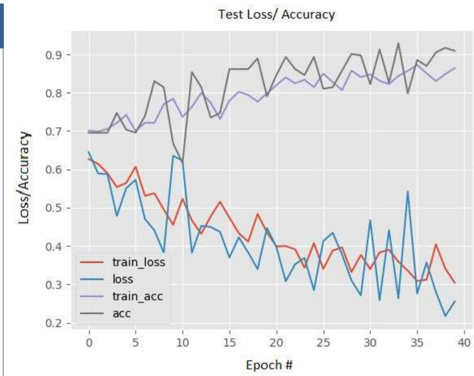

Figure 7: Results using CNN.

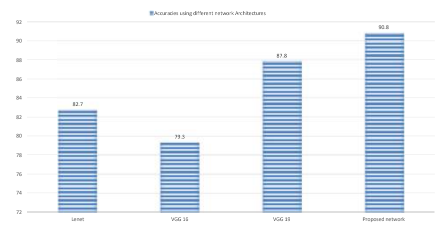

Chart 1. Accuracies using different network Architectures (In %)

Results obtained from Self Organizing map are shown below. It represents clusters of similar polyps formed at the end. Each Cell in this heat-map has a number associated with it which represents it's average distance to neighbouring clusters.

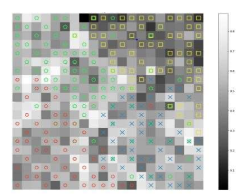

Figure 8: Clustering of different polyp types

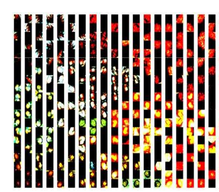

Figure 9: original cluster

Polyp structures which are predicted to be of similar shapes tend to remain closer than those with different. Figure 8 shown above can be further used for real time treatment prediction if proper data is provided.

Conclusions

Thus the CNN Architecture proposed in this paper can be used for efficient classification. Such kind of automatic classification can lead to easy diagnosis of tumor at early stage and further course of treatment can be decided effectively. The kind of treatment given in previous cases can also be provided as input to facilitate automatic prediction of course of treatment using the information on how the actual doctor proceeded in the previous cases of similar polyp structure.