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Novel adenocarcinoma esophagus prediction using deep belief network of machine learning

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Abstract

Adenocarcinoma esophagus detection on early stages is very difficult in traditional imaging detection methods as its spread area is complete esophagus. By using deep learning it become quite accurate than other methods but still in deep learning method scientist uses gradient descent based learning parameter to diagnosis of cancer cells of esophagus, which leads to false negative and positive datasets when high degree of class imbalance is there. In this article a technique which uses a Barrett's esophagus image to predict the adenocarcinoma esophagus with Raven Roosting Optimization algorithm is discussed.

Keywords: Barretts, adenocarcinoma esophagus detection, imaging detection methods, gradient decent.

Introduction

One of the dreadful cancer diseases is Esophageal Adenocarcinoma (EAC), which ranks 7th most frequent cancer worldwide which causes the death. Esophageal squamous cell carcinoma is still most frequent histologic type of cancer [1]. The Barrett's Esophagus (BE), which results from the metaplastic transformation of healthy cells in the esophageal lining into columnar mucosa. It is the most common premalignant source of esophageal malignancy. To diagnose the presence of EAC at its advanced stage, it needs an extremely aggressive treatment and its prediction is poor. Hence, early detection of EAC is very essential but endoscopic diagnosis with while light imaging alone is very tough to detect the presence of adenocarcinoma [2].

The advancement in the field of artificial intelligence along with deep learning created a remarkable improvement in different medical fields, particularly screening the medical images. Deep learning becomes a significant supporting tool in medical imaging, interpreting medical images based on a collected set of exclusive algorithms [3]. Deep learning consents computational approaches with several processing layers to acquire manifold grades of abstraction for image data representations. To construct the deep learning model for detection of EAC, quality of image acquired is very important to recognize the abnormalities in esophagus images very precisely.

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The primary challenge in precise detection of EAC is its appearance and properties as it can be located arbitrarily all over the esophagus tube. The patients have to go for the regular check-ups through examination of endoscopy in order to rheostat the growth of irregularities into later stages. With the growing demand of esophagus images, the computer aided detection system has seized more attention often. Adapting Deep Learning models in medical image analysis has become a standard mechanism for detection, segmentation, classification etc.

Deep belief Networks is constructed by appending the RBM layers as a stack, in which each layer of RBM is communicated to its previous and succeeding layers. Thus, it is a network whichis made up of single layer networks. Apart from the first and final layers, the remaining layers in DBN perform a dual role as hidden layer for the previous RBM and input layer for the succeeding RBM. The DBN is majorly used to cluster, recognize and generate image-based classification of cancerous images.

Related work

Ghatwary et al [4] designed variants of deep learning models to detect the presence of eshophageal adenocarcinoma by applying regional based feature extraction of images on 100 images collected from 39 patients.

Sander Klomp et al [5] in this work computer vision-based techniques are used for detecting the dysplastic tissue in Barret's Esophagus. They applied feature extraction, machine learning methods and classification model with grid search policy to accomplish their task of automated dysplastic and non-dysplastic VLE image detection.

Zhang et al [6] conducted a deep comprehensive survey on impact of artificial intelligence in early detection of adenocarcinoma using endoscopic images. Various deep learning models and computer aided pretrained algorithms are investigated to meet patient centric satisfaction.

Chen-Yi Xie et al [7] stated in their study that using machine learning models to evaluate the treatment response in imaging pertinent to Esophagus cancer detection using radiomic techniques and deep learning models will improve the future applicability of early prognostication.

Kuan-bing Chen[8] in their work developed a deep learning model using convolutional neural network to detect esophageal cancer detection. The characteristic of deep conventional neural network has the ability to filter the features of the entire image, which highly influence the prediction model is highlighted.

Fang et al [9] designed a novel classification model which performspreprocessing using median filter and histogram equalization. The feature extraction is done using principal component analysis and sequential forward selection is used to detect the region of interest. The support vector machine and K- Nearest Neighbours are applied for classification of cancerous and heathyesophageal image.

Luis et al [10] devised a Robust feature detection model to detect the presence of cancerous

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image using SURF based CAD method. The features of the images are extracted using SURF and form the masked areas and Support vector Machine is used for classification.

Souza et al [11] analyzed about the complex pattern of Barrett's Esophagus progression to adenocarcinoma using endoscopic surveillance. The importance of the automated segmentation using machine learning to assist the diagnosis of BE dysplasia is detected using machine learningapproaches.

Horie et al [12] introduced a convolutional neural network to detect the esophageal cancer using image dataset collected from Japan. The convolutional layers with the max pooling, softmax and full connected layer involves in prediction of adenocarcinoma presence in eshophageal image.

Methodology:

Raven Roosting Optimization based Deep Belief Network for Esophageal Adenocarcinoma Prediction

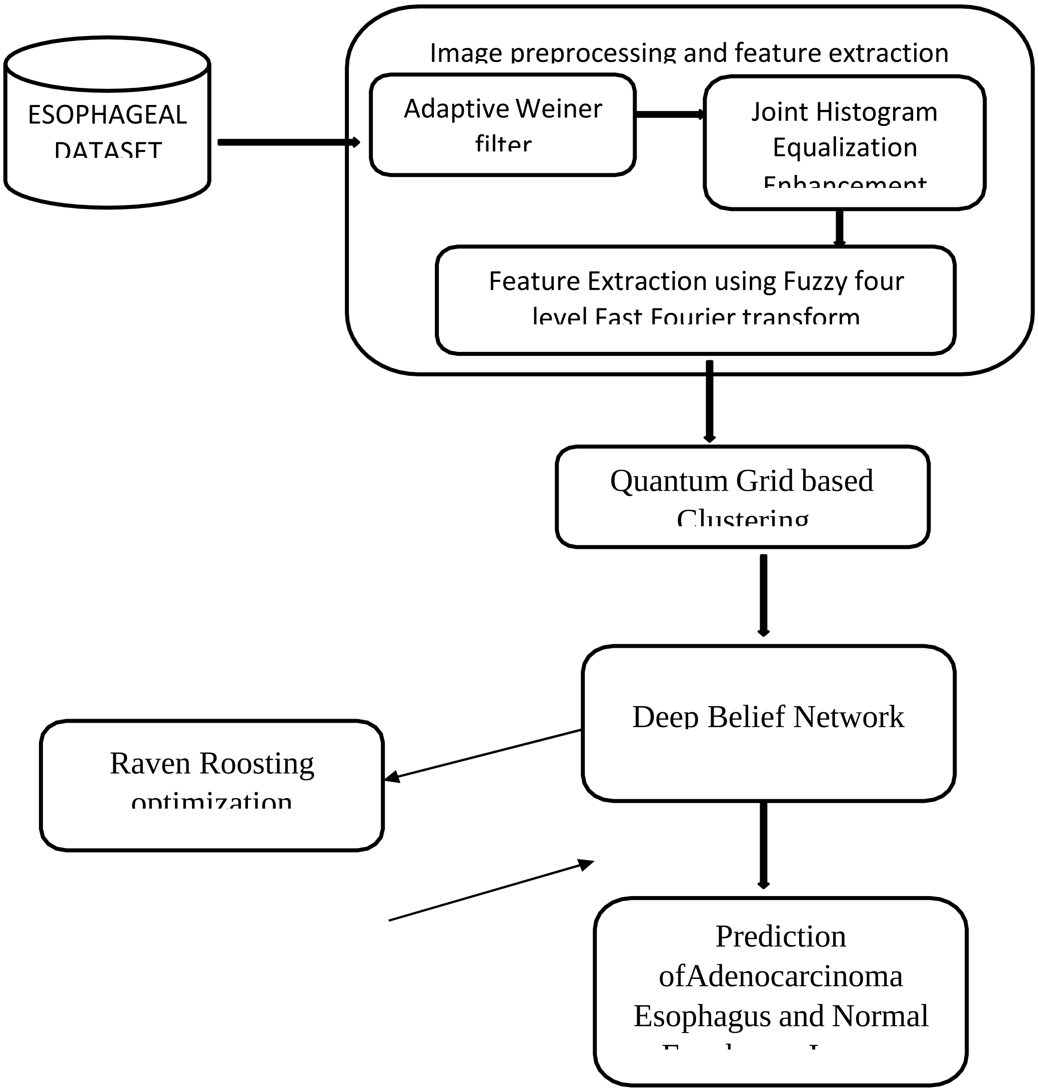

Figure 1: Framework of Raven Roosting Optimization based DeepBelief Network

This method collects image dataset from Endoscopic Vision Challenge MICCAI2015 with 1689 Esophagus images. The image preprocessing is achieved by performing adaptive wiener filtering to denoise the raw esophagus images, the image is enhanced using Joint Histogram Equalization and Fuzzy four level Fast Fourier transform is used for extracting the features for image enhancement and clustering of the esophageal images using Quantum Grid based clustering, for discriminating dissimilar pattern of image and grouping the identical images. The resultant enhanced image is fed as input to the newly constructed Raven Roosting optimized Deep Belief network to predict the presence of Esophagus by depth understanding of the image patterns more precisely. When the voluminous of image dataset is very high, this model handles them more effectively and the parameters used in deep belief network are significantly optimized by adapting the raven roosting algorithm to over the overfitting problem. This model produced highest rate of accuracy compared to the existing standard convolutional neural networks.

Deep Belief Network

The deep learning structure which is constructed using the stack of Restricted Boltzmann machine is known as Deep Belief Network (DBN). Unlike the other deep learning models, the DBN structure is made up of belief network with the logic of RBM. Each RBM comprised of two different layers within itself they are visible layer and the hidden layer. Once the input of the esophagus image is acquired it is passed to the visible unit of the RBM and after the activation function is applied to the input values when it is passed to the hidden layer neurons. Based on the contrastive diverse method they work as an unsupervised method. After learning the features of image pattern, it is passed as the input to the next RBM and it is repeated until it reaches the last RBM of the stack. Once, the complete network completes its learning phase, and then it acts the supervised model to classify the instance as adenocarcinoma esophagus or healthy esophagus.

The softmax layer plays as the supervised model which classifies the images as either normal esophagus or it is an adenocarcinoma affected esophagus. Excluding the first and the last layer, the intermediate layers of DBN plays a dual role namely hidden layer for its previous RBM and the input layer for the succeeding RBM. While learning the parameters of the first layer "RBM", the ascending weights are forced to double the descending weights as illustrated in the figure 2. Intuitively, using the weights (W) twice when deriving the state of hidden units h compensates for the initial lack of top-down feedback. On the other hand, during the preprocessing of the last "RBM"of the stack, the descending weights are forced to double the ascending weights. For all intermediate RBMs, the weight is halved in both directions when composing to form the DBM.

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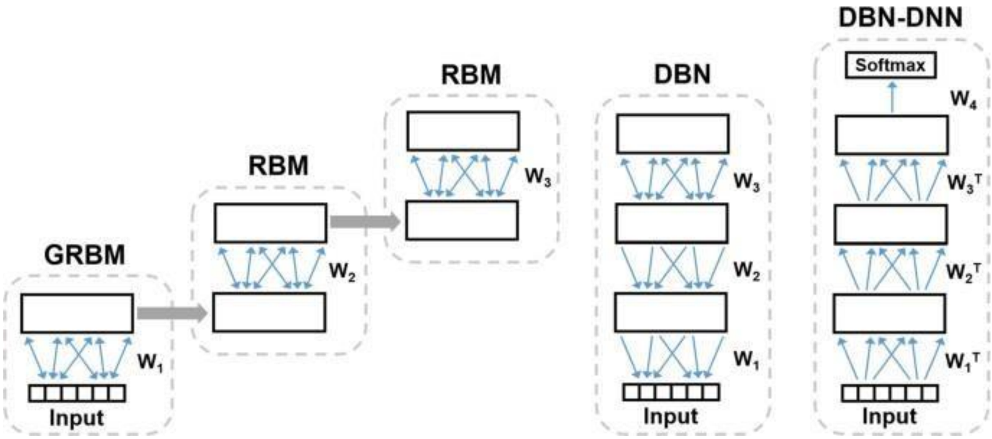

Figure 2 Structure of Deep Belief Network

Raven Roosting Optimization

The presence of uncertainty in searching location and food resource with high quality necessitates the organisms to build a searching strategy to discover them. Providing success in foraging is highly essential for all organism survival with better quality of strategies during the process of evolution. Roosting is a kind of social behavior which is exhibited by few animals including birds, they come together to rest. Based on the behavioral inspiration of raven roosting the algorithm Raven Roosting Optimization is developed whose objective is to choose theroosting site in a random manner.

Initially, a set of raven ‘M’ is selected from the population and they are positioned at the random location in the search space. Each of the position isrelated to the significant food resource location. The fitness value of M locations is evaluated and best solution’s location is marked as the leader. Next, the information sharing step is mimicked as a primary process in roosting. Like real world raven roosting, only a small ratio of roost members will be selected to a new food source, while rest of the members in the roost will endure to private food location in a trial and error food searching. A ratio of the raven’s ‘q’ is recruited to leave the roost and follow the leader. Perhaps, the recruited follower is able to perceive radius hypersphere around the leader and it may forage for better location when it is discovered by them. The personal best memory for each bird offers the concept of private information instead of piggy back broadcast from the LEADER.

In addition,with flying to intended destination, each bird continue to seek for new food source enrooting. The process is simulated by partitioning their flight into M steps, where the length of each step is selected arbitrarily, the birds position is updated and represented mathematically as

$$cp_{j,s} = cp_{j,s-1} + dt_{j,s}$$

where $cp_{j,s}$ is the jth raven’s present position, $cp_{j,s-1}$ is its previous position and random step size is denoted by $dt_{j,s}$.The range of radius around its environment is denoted by Rp and

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arbitrary perception is represented using Np. When a bird detects a better location than its personal best position then raven stops its flight at that time and forages to the newly discovered location. Else it moves towards another step till it reaches its destination.

The deep belief network is trained using the raven roosting algorithm instead of greedy learning which involves in training of a single RBM at a time and continues till reaches the last RBM. The visible layers of RBM receives the BE image, where the visible layers have undirected connections with the hidden layers. The raven roosting optimization algorithm assigns the best values using its food searching behavior to optimize the process of learning phase. The significant features of the esophageal image are extracted using the knowledge of restricted Boltzmann machine with the knowledge of detecting adenocarcinoma with the precise region of interest in esophagus. Thus, the best fittest values of weight highly influence the process of EAC detection at its earlier stages. The figure 3 illustrates the overall architecture of the Raven RoostingOptimization Algorithm based Deep Belief network for adenocarcinoma esophagus prediction.

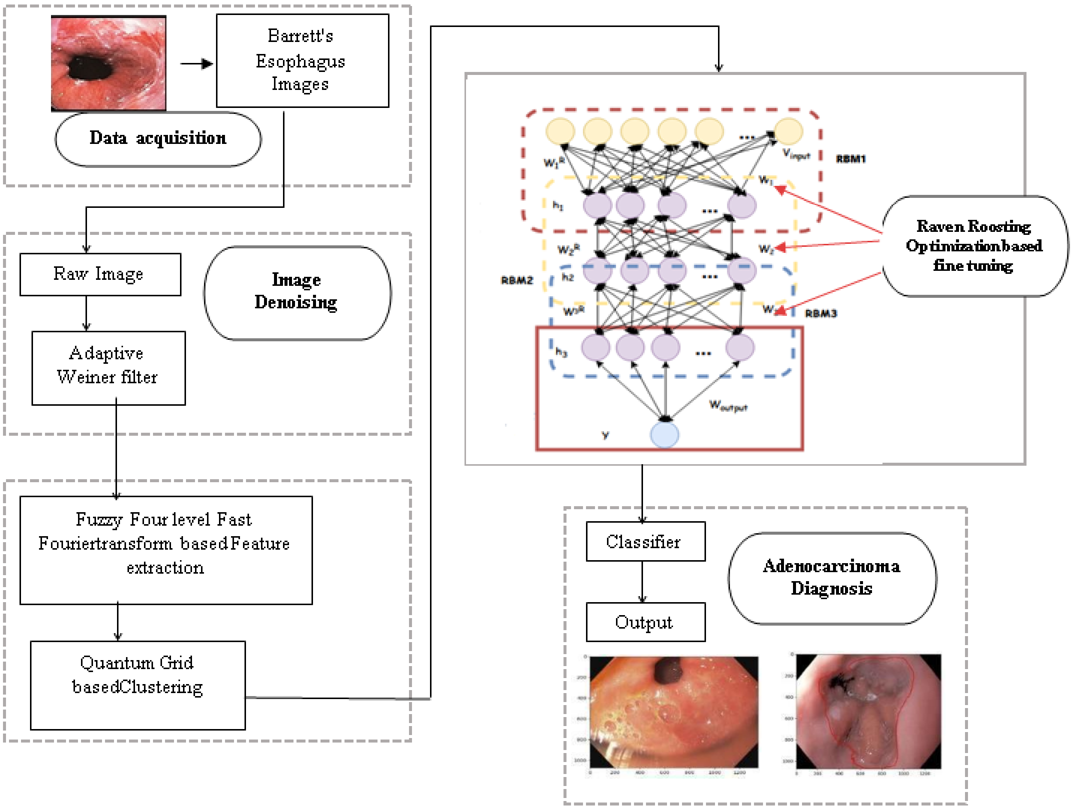

Figure 3.Detailed work flow of RRO-DBN for Adenocarcinoma Esophagus Detection

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Results

The dataset is collected from Barret's Esophageal imagesto detect the presence of Adenocarcinoma disease. To evaluate the efficiency of RRO-DBN algorithm the metrics used are accuracy, precision, recall and mean square error. The all four algorithms comparing performance metrics i.e. RRO- DBN, Multi-Layer Perceptron (MLP), Deep Neural Network (DNN) and Convolutional Neural Network (CNN). The table depicts the performance comparison based on Accuracy, Precision, Recall and Error Rate for Adenocarcinoma Esophagus Detection.

Table 1: Performance Comparison

	Accuracy	**Precision**	**Recall**	**Error Rate**
MLP	0.793	0.784	0.778	0.0518
DNN	0.815	0.799	0.789	0.0394
CNN	0.917	0.897	0.891	0.0238
RRO- DBN	0.985	0.972	0.969	0.0061

Conclusion

This paper focuses on discuss the adenocarcinoma esophagus prediction using deep belief network its performance is enriched by adapting the raven roosting optimization algorithm. The raw esophagus image resolution is improved using adaptive noise filtering and the fuzzy fast fourier transformation-based feature extraction. The significant feature information is extracted using quantum grid clustering and fed as input to the DBN. The performance of the deep belief network primarily relies on the parameter involved in training phase to learn about the pattern of significant features in the esophagus image. The raven roosting behavior with its best fittest value in searching of best solution is adapted in each stack of the RBM to empower the learning rate of the DBN to detect the presence of adenocarcinoma in esophagus images.

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