International Journal of Aquatic Science
ISSN: 2008-8019
Vol 12, Issue 03, 2021

Detection Of Oral Cancer In Hyperspectral Images Using Restricted Boltzmann Machines

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Abstract. Oral cancer is one of the dreadful diseases that affect the people of ages above 40 in most cases. It affects the regions around the mouth especially the back part of mouth which can lead to death often. There are various compu- tational techniques available to detect this widespread disease at the later stage only. If the disease is detected at an earlier stage, then the survival rate of the victims can be increased to 5 years. This paper focuses on detecting oral can- cerous cells at an earlier stage using deep learning techniques as they work ex- tremely well for image recognition and image classification. An intelligent technique comprising of Restricted Boltzmann Machine (RBM) is applied for differentiating the benign and malignant tissue in hyperspectral images (HSI). After experimental results, accuracy obtained was 95.75% using the proposed enhanced RBM technique..

Keywords: Deep Learning, Hyperspectral Image Classification, Oral Cancer, Restricted Boltzmann Machine.

1. INTRODUCTION

One of the main oral cavity tumors is Squamous Cell Carcinoma (SCC), oth- erwise called as Head and Neck cancer. This term is used to describe tumors that occur in the regions of head and neck such as mouth, salivary gland, throat and nose. Amongst these regions, most cases were reported in the areas of mouth and throat, called as oral cancer. The major cause for oral cancers is usage of tobacco leaves for prolonged years and also alcohol in some cases. It is very difficult to detect the pres- ence of malignant cells at an earlier stage. Symptoms of this disease include difficult to speak, eat, breathe, loss of appetite and especially pain in the affected regions. This disease is common among the developing nations in and around Asia due to lack of awareness among the socially backward people. Also, it has been showing up a rapid pace in American and European nations also. Every year, more than half a million people are diagnosed with SCC of the head and neck worldwide [1].
Deep learning affords precise classification and surpasses human classifica- tion standards for a large data set of images. These techniques mainly include Convo- lutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Restricted Boltzmann Machines (RBM), Deep Belief Networks (DBF) and Autoencoders. In this paper, RBM is used for detecting oral cancer. All these deep learning methods are
extensively used for a very large image data set and provide precise classification and also surpass the traditional classification techniques [2]. In the proposed work, RBM is used which contains one layer of hidden units and restricts connections between the hidden units

[3] and hence it makes the learning process more efficient.
Nowadays cancer detection methods use variety of medical imaging tech- niques to detect presence of malignant tissues in the human body. Some of the widely used medical imaging techniques are Radiography imaging, MRI-Magnetic Reson- ance Imaging, 1Ultrasound imaging, Endoscopy, PET-Positron Emission Tomography imaging and hyperspectral imaging. In the proposed work, hyperspectral imaging is used for more accurate classification. Currently, the HSI classification based on deep learning has gained considerable attention in the field of medical analysis and achieved good results [4]. Deep learning obtained higher probability for intelligently classifying HSI [5]. The focus of this paper is to propose an enhanced RBM technique for detection of oral cancerous tissues using the HSI processing technique. For valida- tion, the experimental results are compared with traditional medical image classifica- tion methods like CNN and Support Vector Machine (SVM).

2. RELATED WORK

Hyperspectral Imaging (HSI) can obtain a collection of medical computer- aided images in various adjacent narrow spectral bands and restructure the reflectance spectrum for every pixel of the HSI [6]. HSI has the advantage of providing enough deep knowledge concerning various tissue parts and their spatial distribution from the spectral feature of each pixel in the hyperspectral image [7]. Thus, HSI processing can be used for non-invasive detection and diagnosis of a variety of cancers such as oral cancer, breast cancer, cervical cancer, gastric cancer, lung cancer and so on [8].
Comparing to the conventional machine learning algorithms, deep learning models with multiple abstraction levels can learn data representations more efficiently and also ascertain complex structures in high-dimensional data [9]. Computer-assisted detection and diagnostic system with high computational power is built for the processing of large volumes of complex data [10]. For very large image datasets, deep learning algorithms offer precise classification and also surpass human level classifi- cation standards [11]
In the field of deep learning, Restricted Boltzmann Machines (RBMs) were thoroughly studied and extensively used [12]. These are typically the basic artifacts of deep learning systems [13][14][15], such as Deep Belief Networks (DBNs) [16] and Deep Boltzmann Machines (DBMs) [17], for instance. Especially, RBMs were demonstrat- ed to prove that they possess the universal ability to approximate discrete distributions [18]. It is also possible to configure RBMs for carrying out collaborative filtering activities [19].
All these facets formulate the RBM an appropriate deep learning technique for the simulation of the input data's complex statistical features. As a consequence, various improvements have been made in a variety of applications based on the origi-
nal RBMs. For example, Replicated softmax models are used widely in documents to model word distributions and also focus on extracting the latent topics [20]. RBM based models has also been used to accurately predict drug-target interactions in the field of Bioinformatics [21]

1.1 Restricted Boltzmann Machine (Rbm) Architecture

RBMs are generative neural networks consisting of two (visible and hidden) layers of neural networks upon which the learning process is carried out in an unsu- pervised manner [22]. The supervised learning algorithms have shortcomings such as lack of sample, classifying low proportion of cancer pixel information, complexity of data, etc. Thus, unsupervised learning is appropriate for constructing medical image analysis than supervised learning. The only difference between RBM and the classical Boltzmann Machine [23] is that there is no links connecting the neurons present in the same layer of RBM. Fig. 1 illustrates the structural design of a RBM, which consist of a visible layer v with m number of units and a hidden layer h with n number of units. The real-valued mxn matrix W represents the weights involving visible layer and hidden layer neurons, where w_{ij} correspond to $_1$the weight connecting the visible layer unit v_i and the hidden layer unit h_j. [22]

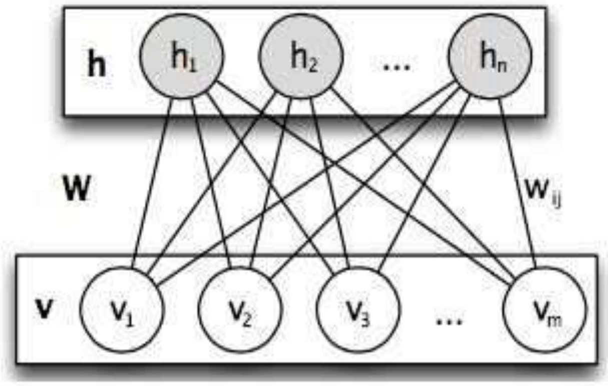

Fig.1. Structural Design of RBM [22].

1.2 Hyperspectral Image Analysis

Detecting tumor margins can be difficult during traditional clinical analysis. Hyperspectral image analysis is used in many of the healthcare monitoring systems
that analyses large volume of data for discovering the malignant tissues that causes cancer in victims. This HSI processing utilizes Subband Coding (SBC) data reducing method for hyperspectral imaging systems. The HSI processing can be performed using the suitable learning algorithm with a small wavelength subset and a non-linear combination of spatial and temporal values. Also, data mining algorithms can be used to retrieve spectral information. This HSI system generates high resolution multispec- tral imaging (MSI). In HSI, every pixel is represented by a vector whose entries match with different responses to the spectral band. [24].

a. Pre-Processinh

Pre-processing is executed on the hyperspectral image dataset for identifying the non-relevance of the input signal being pre-processed in the formation of the data set[25]. As a result of pre-processing step, the hyperspectral images in the dataset will contain only the vitally abstracted features for image classification using RBM. This preprocessing step is required because the hyperspectral data in grey scale format is complex to process[26][27]. The HSI images are normalized to recline in the pixel of the range [0,1] that has been changed to [0,512]. This results in conversion of the HSI to its standard size meant for the proposed neural network design. Finally, each hyper- cube is created by data augmentation from the spatial information of the image with dimension X x Y x Z, in which X, Y and Z corresponds to height, width and number of volumetric channels.

1.3 Feature Extraction and Feature Selection

After pre-processing is completed, the process of feature extraction, followed by feature selection is performed on the highly abstracted features present in the hyperspectral image dataset. By representing the data in a reduced sub-space dimen- sion, extort the necessary feature of the data. When the feature extraction process is completed, the next step is to select the features used for classifying the benign and malignant tissues represented as data in the input layer of the network. Therefore, a collection of features from the dataset$_1$of reduced dimension compose an excellent model of learning for given data.

1.4 Image Classification

After feature selection is completed, the next step is to classify the image us- ing RBM. The classification is executed on the basis of derived features. This com- plete procedure is represented in the flowchart shown in Fig.2.

In this step, the pre-trained features are used by the RBM binary classifier for classifying the prediction results into two classes namely, benign and malignant. Be- fore feeding the RBM classifier with the features selected for classification, the pre- trained oral data samples is partitioned into training set (65%) and testing set (35%). Accordingly, the RBM classifier is trained by using the training dataset in order to predict the results with or without oral cancer. Based on the trained RBM model, the
oral sample data in the testing set are classified and belongs to one of the class, either benign class or malignant class.

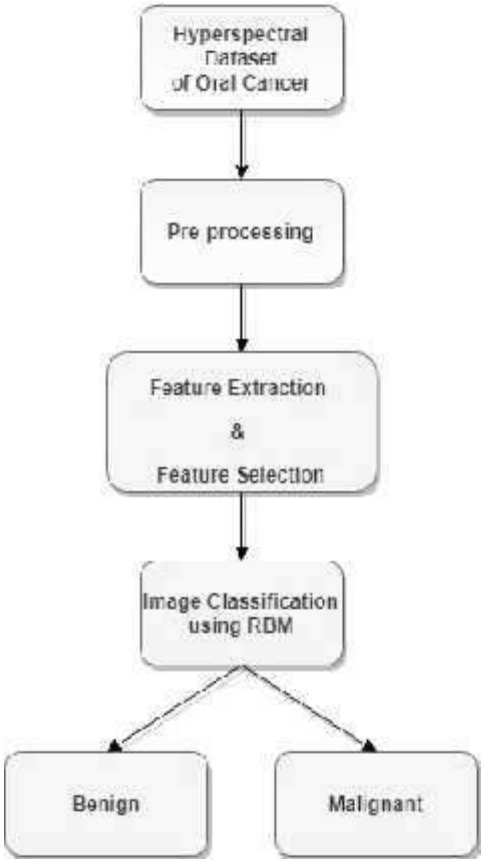

Fig.2. The Proposed Model.

2. RESULTS AND DISCUSSION

We explain the experiments executed to analyze the rationale of the pro- posed method in this section. Performance index verification by using metrics such as accuracy, specificity and sensitivity prediction per image patch are examined. Boltzmann distribution is used for initializing the weight factor and it is trained using backpropagation algorithm in the units of visible layer to the units of hidden layer and the output layer in the network. Comparison with standard techniques such as CNN and SVM for the same dataset is also performed to check the efficacy of the proposed method as given in Fig.3. The comparison results of RBM, CNN and SVM is given in table 1.

Table 1. Comparison results.

Classification Model	Sensitivity	Specificity	Accuracy
RBM	93.26%	94.74%	95.75%
CNN	82.32%	78.46%	89.40%
SVM	80.61%	75.56%	88.98%

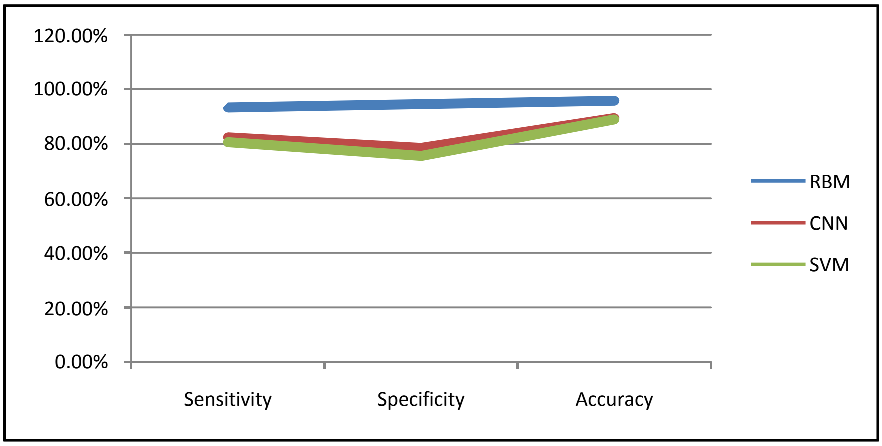

Fig.3. Comparison chart.

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