Journal of Cancer Research and Clinical Oncology (2019) 145:829–837
https://doi.org/10.1007/s00432-018-02834-7

ORIGINAL ARTICLE – CANCER RESEARCH

Computer-assisted medical image classification for early diagnosis of oral cancer employing deep learning algorithm

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Received: 4 November 2018 / Accepted: 24 December 2018 / Published online: 3 January 2019

Abstract

Purpose Oral cancer is a complex wide spread cancer, which has high severity. Using advanced technology and deep learning algorithm early detection and classification are made possible. Medical imaging technique, computer-aided diagnosis and detection can make potential changes in cancer treatment. In this research work, we have developed a deep learning algorithm for automated, computer-aided oral cancer detecting system by investigating patient hyperspectral images.

Methods To validate the proposed regression-based partitioned deep learning algorithm, we compare the performance with other techniques by its classification accuracy, specificity, and sensitivity. For the accurate medical image classification objective, we demonstrate a new structure of partitioned deep Convolution Neural Network (CNN) with two partitioned layers for labeling and classify by labeling region of interest in multidimensional hyperspectral image.

Results The performance of the partitioned deep CNN was verified by classification accuracy. We have obtained classification accuracy of 91.4% with sensitivity 0.94 and a specificity of 0.91 for 100 image data sets training for task classification of cancerous tumor with benign and for task classification of cancerous tumor with normal tissue accuracy of 94.5% for 500 training patterns was obtained.

Conclusions We compared the obtained results from another traditional medical image classification algorithm. From the obtained result, we identify that the quality of diagnosis is increased by proposed regression-based partitioned CNN learning algorithm for a complex medical image of oral cancer diagnosis.

Keywords Deep learning algorithm · Medical image classification · Hyperspectral image data · Image labeling · Oral cancer diagnosis

Introduction

In recent decades of cancer reporting, oral cancer is most reported cancer of 4.5 million as in 2017 by social economic groups by world health organization; approximately 85% are responsible for death. Early detection will lead to 70% reduction in death rate (Bradley et al. 2018). Hence, in Computer-Aided Diagnosis (CAD) the medical image plays a vital role for detecting. For cancer detecting by medical imaging techniques Hyperspectral Imaging (HSI) is extensively used for detecting organ at risk. Also, this multidimensional imaging technique is most practiced by most of the oncologists (Baljit Singh et al. 2016). Computer-aided detection and diagnosis system with high computing capacity is developed for processing large amount of complex data (Prochzazka et al. 2017). Moreover, for the design of such system, a high processing algorithm is needed for data classification (Christodoulidis et al. 2017). By training the algorithm with knowledge of the experts and testing the trained network of remaining image data set will provide an advanced classification technology. For that a highly advanced computing technique is adopted.

Deep learning provides accurate classification and exceeds human level of classification for a very large image data set (Dey et al. 2017). In this paper we design and develop a partitioned Convolution Neural Network (CNN) to match the performance of the experts on classification of benign and cancerous image. Since the deep learning

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algorithm provides less feature to train and provide more efficient learning tool (Deepak Kumar et al. 2018). To validate the effectiveness of classification, we compare with conventional techniques like SVM (Dou et al. 2016) and Deep Belief Network (DBN). From the head-to-head comparison, our proposed partitioned CNN outperforms other state-of-art classifying techniques by classifying accuracy, specificity, and sensitivity. We learn features to detect tumor by treating benign abnormalities. These are considered as false positive about framing confusion matrix.

The main objective of this paper is to design a partitioned deep CNN algorithm for classification of oral cancer filtering into the HSI imaging. Then to validate we compare with other conventional medical image classification technique like SVM and DBM methods. The block diagram of proposed image classification technique is shown in Fig. 1. From the block diagram we can understand the various processes involved in designing an automated oral cancer classification using deep learning technique.

The remaining section of this research article is presented as follows: the background works and the literature of existing methods are presented in second section. Formation of data set and proposed partitioned deep CNN algorithm is explained in third section. The fourth section describes the experimental verification and comparison between other conventional methods. Fifth section presents the results and discussion and sixth section provides the conclusion of the research paper.

Background and related work

In this section, we summarize some related work in medical image classifications (Heba et al. 2018). The authors discussed about the importance of cancer detection. They listed the number of cases reported on different cancers subjected and explained how the artificial intelligence technique helps to increase the detection of cancer. They perform the classification of brain tumor by standard test image of UCI machine learning data set. From their work we identified the problem of cancer to socioeconomic people. They obtained accuracy of 87.2% for detecting brain cancer using deep neural network. In Philippe et al., the survey of various applications of deep learning towards the implementation of different learning method used for medical image classification. Moreover, the advance computer-based computing technique making the classification effective was discussed. The hyperspectral imaging application for cancer detection over other medical imaging technique was discussed in reference by Deepak Kumar et al. (2018). They compared many imaging methods of cancer detecting and explained the advantage of hyperspectral image. Hence, HSI can use for medical experts on classification. They performed classification using Support Vector Machine (SVM) by self-organizing map structure.

In the work of Yuan et al. (2015) and Dou et al. (2016) how the HSI outperforms other imaging methods like MRI and CT is given. Also, they used detection of cerebral bleeding by deep learning algorithm in their application. In reference Wang et al (2017), semi-automated method to classify the cancer by deep learning algorithm was discussed. They used stacked auto-encoder for classification in the work of Kalantari et al. (2017), explaining the application of hyperspectral for detecting lung cancer. They used the CNN for image segmentation.

From this background work in cancer detection lack of full autonomous system design for cancer detection by deep learning technique is identified. Most of the techniques need advanced configuration system which results in high cost of system operation. We overcome the challenges described in Yuan et al. (2015) by providing a regression-based structure of convolution neural network of automated cancer detection system in available hyperspectral medical image using this novel deep learning algorithm.

Materials and methods

Data set formations and feature extractions

For the accuracy improvement in classification among the several methods of data formulations, we select the bagging and boosting method (Haimiao Ge et al. 2018). This method combines the output from decision tree and

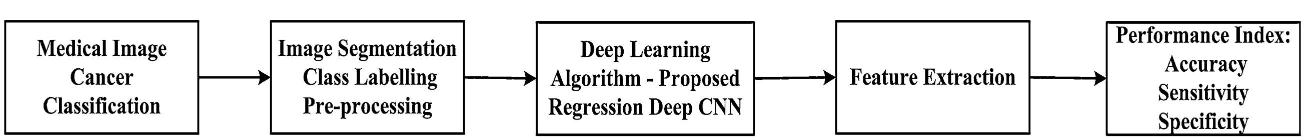

Fig. 1 Block diagram of various process involved for proposed regression-based CNN for oral cancer classification

selects the final feature based on votes of weight. In the boosting method, the weight of training data is combined based on votes from each data set. Bagging and boosting the cancerous hyperspectral image data set used for cancer classification.

For hyperspectral image training, we used standard data sets of BioGPS UCI repository for extracting normal data set. The data set for image classification is represented by vector set$\mathbf{D} = \sum_{\mathbf{i}=1}^{\mathbf{d}} \{\mathbf{x}, \mathbf{A}\}$, each data cube is given by $\boldsymbol{x} : \boldsymbol{\Omega} \rightarrow \mathbb{R}$ and the region of tumor is represented by $\boldsymbol{A}_i = \{\boldsymbol{d}, \boldsymbol{y}, \boldsymbol{C}\}$ where, dimension $\boldsymbol{d} = \{\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{l}, \boldsymbol{h}\} \in \mathbb{R}$ and $(\boldsymbol{x}, \boldsymbol{y})$ is the position of 2D coordinate, $\boldsymbol{l}$ represents length and $\boldsymbol{h}$ indicates height of tumor in image patch. Each image patch is defined by the boundary $\boldsymbol{d}_{ij} \in \{0, 1\}$. This class label denotes the region is either cancerous or benign, regions with no boundary are considered as normal tissue. No malignant detected normal tissue is denoted by $\boldsymbol{A}_i = \emptyset$.

The Region of Interest (ROI) is detected by boundary $\left\{\boldsymbol{d}^*\right\}$ and marked $\{\boldsymbol{y}^*\}$ for a single image patch HSI $\boldsymbol{x}$ is given by $\sum_{n=1}^{N} \left\{\boldsymbol{d}^*, \boldsymbol{y}^*\right\} = \boldsymbol{f}\{\boldsymbol{x}, \ \boldsymbol{\theta}_{\mathrm{ROI}}\}$ where N is the set of tumor present. This feature vector is used for detecting cancer segment of CNN. The true positive predicted by the image patch are $\left\{\boldsymbol{d}^*, \boldsymbol{y}^* \ \right\}$ and presented in the input layer of deep CNN for classification.

Selected feature for classification of oral cancer in HSI image

Most of the medical images are classified based on intensity. But we deviate from this by increasing the classification accuracy. The image intensity values along with texture information about spatial and spectral information are considered in the hyperspectral image of oral cancer person. Since, HSI is a multidimensional frequency spectrum of different bandwidth. We include voxel under consideration with three-dimensional axes and probability information. The spatial location of voxel $\boldsymbol{V}$ and neighborhood image intensity are used for classification. This configuration includes the three-dimensional cubic patches of hyperspectral image.

Structure of proposed partitioned deep CNN architecture

In the proposed medical image classification system, the challenges to designing an accurate classifier are:

- It is able to process feature map of less variation complex mapping vector feature map.
- It is able to process a real time series data in available Random-Access Memory (RAM).

Hence, the proposed CNN is a supervised network which uses optimum data onto training the network of partitioned structure. For this we employed a complex regression-based training procedure for training multidimensional hyperspectral image to detect cancer ROI. From the Google Net Inception V3 CNN architecture, the pretrained CNN is modified by the regression-based partition convolution and sub sampling layer. Figure 2 shows the training of deep CNN by labelled data cube.

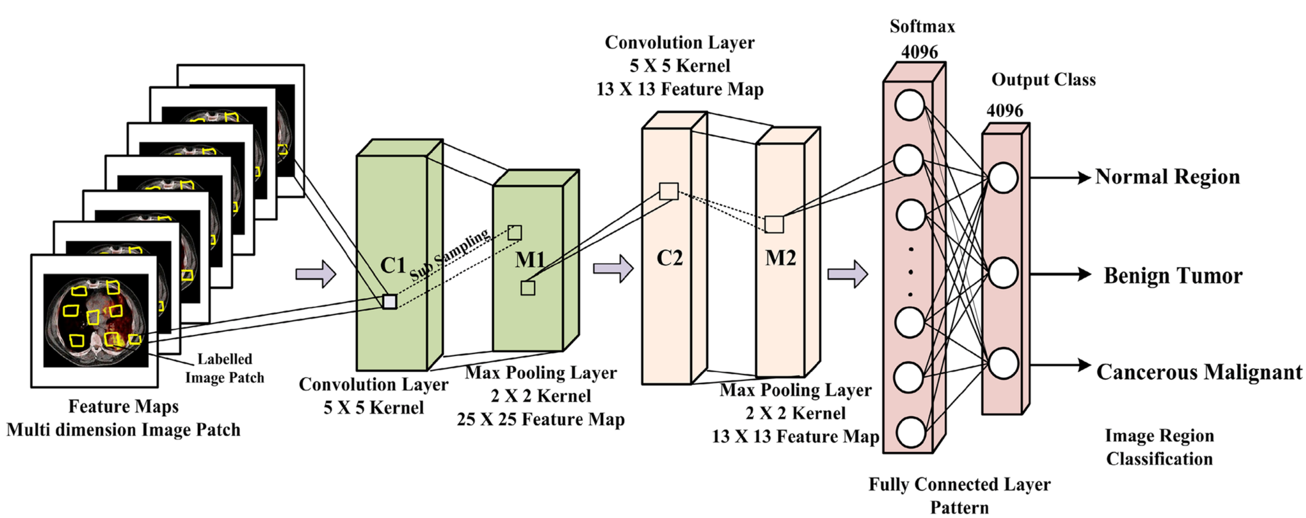

Fig. 2 Illustration of proposed regression-deep CNN with number of kernel used for classification. Two partitioned structure of CNN with kernel size, feature map and three-way classification in output layer

Before the patches are segmented, by the proposed partitioned regression CNN, we label the patch by the size 250×250 pixel values. This class of supervised forward networks is given by

$$F(x) = F_N\left(F_{N-1}\left(\ldots\ F_1(x)\right)\right) \tag{1}$$

where N, indicates number of hidden layers. The proposed deep CNN consists of input layer, two functional layers which has C1-first convolution layer, M1-first pooling layer, C2-second convolution layer, M2-second pooling layer and one fully connected layer. In the input the feature vectors image patch is presented. The convolution layer consists of multiple kernels of 5×5 size. To reduce progressive size M2- produces nonlinear down-sampling by 2×2 size kernel. The fully connected have 1×1 kernel of SoftMax prediction. This network structure is described in Fig. 2. Hence, using GoogLeNet structure we can process complex structure inception by two convolutions and two max pooling.

Table 1 Data set information for training proposed deep CNN model

Data set	Data set repository	Sample information for training		
		Tumor	Normal	Total image patch count
BioGPS data portal	UCI machine learning repository	65	35	100
TCIA Archive	Standard	450	50	500
GDC data set	Standard	625	75	700

Hyperspectral cancerous image analysis

The proposed regression-based partitioned deep CNN algorithm was implemented on hardware with following specification: intel processor i7, 64 GB RAM with NVIDIA GeForce GPU, 1 TB hard disk for implementing. From this configuration we built an autonomous intelligent malignant classification system. The classification algorithm for proposed CNN is described by algorithm 1. Table 1 shows the data set used for training the designed algorithm in training phase. This data set makes the learning of network of the workbench, and then in the next phase of testing the unclassified data set is presented in trained network of the region of interest classification. We have made the three-way region of interest in classification. Figure 3 shows the training and testing phase of proposed regression-based CNN.

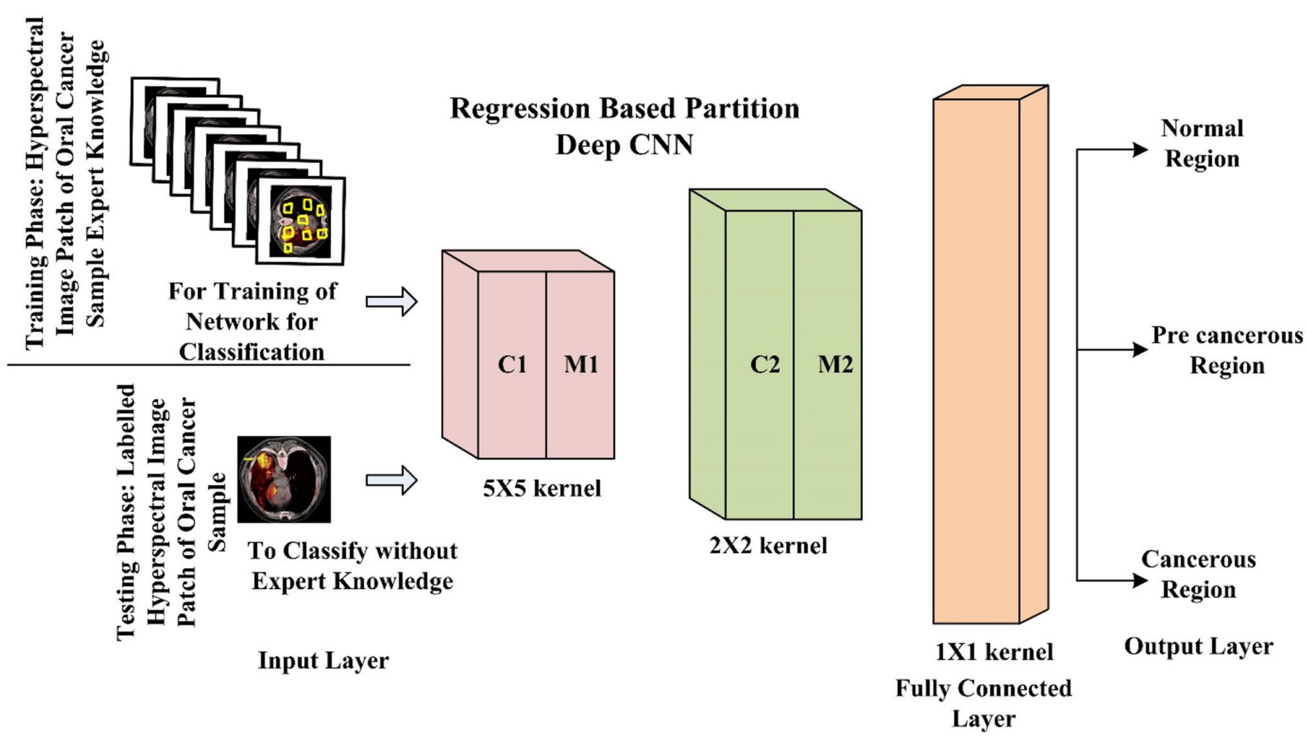

Fig. 3 Training by 1028 HSI image patch and testing of oral cancer for classification

Algorithm 1: Cancer Image patch refinement Deep Learning algorithm

1: Input: hyperspectral image x, labelling by $D = \{d, f\}$, boundary d_{ij}, number of iteration N, threshold A_j, maxclass size (int), matching function θ
2: Procedure for image patch (d, f)
3: for t=1,2…N do
4: $A_i = \{d_{best}, f_{best}\} \in \mathbb{R}$
5: for $x = \sum_{i=1}^{N}\{x, A\} \geq A_i$
6: $B_{new} \leftarrow B_{n+1} \in \mathbb{R}$
7: if image $\{d, f\}$ <classification then
8: $A_i = \emptyset$
9: else
10: for $t = t + 1$ do: f< image size
11: append class label
12: $d_{N+1} = argmax(d, \theta_E)$
13: for b=1,2… N do
14: $(W_{New}, \rho_{New}) \leftarrow Z(D, L, x, y)$
15: end for
16: $\theta(max) \leftarrow reweight(\tau(v), I)$
17: end for
18: end for
19: end if
20: $B_{new} \leftarrow B_{old} \cup B_{new}$
21: end for
22: update the kernel value $\theta = argmax \sum^{N}\sum^{B} l(x, y, \theta)$
24: compute initial distance $\emptyset$
25: compute pairwise labelling to feature map.

This algorithm forces the segment less than class size. The image classification algorithm uses a high-resolution hyperspectral image patch. The bounding box $B_{\text{ref}} \in D$ is searched by refinement algorithm. The patch size $N \times N$ has the empirical loss if;

$$\theta = \arg\min \sum_{i=1}^{D} \sum_{i=1}^{B} l(x, y, \theta) \tag{2}$$

here i is the index of training patch.

The partition in max pooling layer is given by

$$E = \sum_{k=1}^{N} \theta(y_i, x_i) \tag{3}$$

where $\theta = (y_i, x_i)$ is label point corresponding to image patch.

The activation function was sigmoid and given by;

$$f = \max(0, x) \tag{4}$$

with pixel-wise rectified linear unit nonlinear activation function. This proposed deep CNN structure is implemented in hyperspectral image of oral cancerous region for classification.

Experimental verification of proposed deep learning algorithm with hyperspectral image data set

Testing image analysis

We first applied the data to input layer of CNN from which the feature vector is formed by sevenfold cross-validation technique. Then the convolution and max pooling produces the first-stage training. The dimension of feature map is reduced by sub sampling. The confusion matrix for proposed deep CNN of three-way classification. The training partition varied from 10 to 90% and in testing phase. In the confusion matrix, a first row is malignant and second row is benign tumor and third row is normal tissue region. The distribution is given by demonstrating malignant tumor with normal and benign with normal. Figure 4a shows confusion matrix by expert data set training by examination of image sample. Figure 4b, is the matrix by conventional SVM classifier and Fig. 4c, is DBN classification and Fig. 4d, is matrix for regression-based partition deep CNN classifier algorithm by same image data set.

Verification with other classification technique

For verification and evaluation of proposed regression-based deep CNN we used SVM and DBN. In this cross verification, we use the same data set formed by Sect. 3.1. The number of hidden layers in Deep Belief Network (DBN) is high than the fully connected layers. It contains multiple hidden layers. The DBN structure has weight symmetrically within the layer. It learns by restricted Boltzmann machine defined by $P(v|h,\ w)$ and has probability-based linear distribution given by:

$$P(v) = \sum_{h} P(h|w) \tag{5}$$

the weight update between visible layers when input is presented and weight change is given by:

$$\Delta w_{ij} = \rho[P(v, h)] \tag{6}$$

DBN is also a highly precise deep leaning algorithm for complex medical image classification for the following reasons:

1. It has fully connected supervised learning structure.
2. It learns feature vector and pretrained for presented input.

Hence, DBN is used for same data set for classifying oral cancer hyperspectral image for performance verification. To visualize the classification of hyperspectral

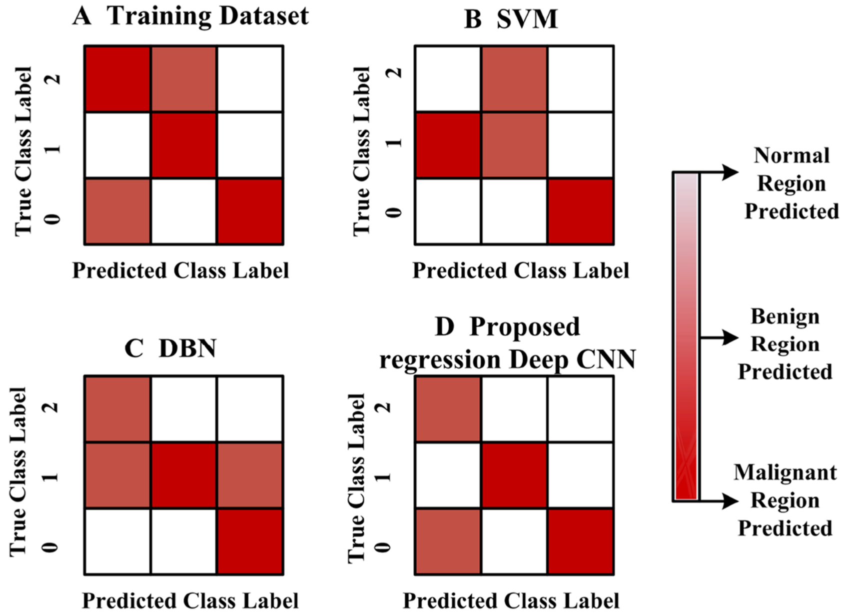

Fig. 4 Confusion matrix for calculating performance index and classified data confusion matrix by SVM, DBN, and regression-deep CNN

image of oral cancer, the data visualization for three classes is shown in SNE visualization method. The scatter plot of classified data visualization is present in Fig. 5, it shows how the proposed regression-based partitioned deep CNN classifies oral cancer. In Fig. 5, red point indicates the cancerous segment. The green points indicate the benign pre-cancerous region. The yellow dot represents normal image segment of image patch presented in input layer for classification.

Result and discussion of proposed regression-based partition deep CNN algorithm for oral cancer classification

To evaluate the proposed algorithm, we verified the obtained result and model in several standard data sets and expert knowledge. The use case we performed, whether the cancer classification is distinguished as cancerous region or

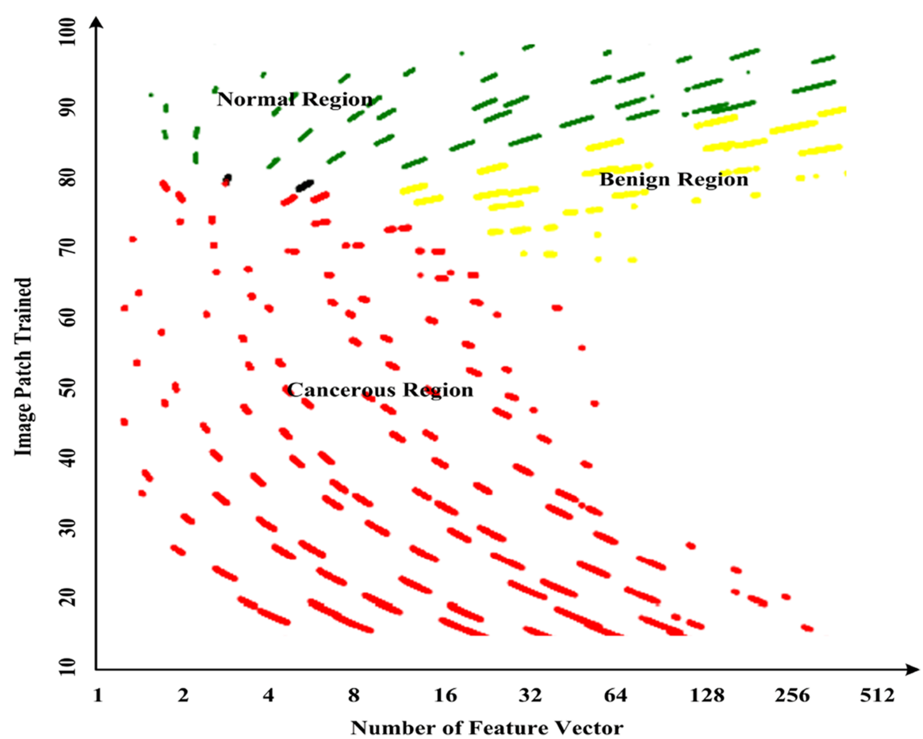

Fig. 5 Scatter plot using Stochastic Neighbour Embedding for data visualization by deep CNN method to hyperspectral image for three-way classification

normal region in medical image. Also, the benign condition also predicted by deep CNN. We perform four trials one with standard image and other three class of oral cancer. The performance evaluation is done based on sensitivity, specificity, and classification accuracy.

The confusion matrix is derived based on Fig. 4;

1. True positive, total number of post cancerous malignant detected. Positive number, number of cancerous subjects presented in the input layer.
2. True negative, total number of predicted benign region. Negative number, number of benign subjected presented in the input layer.

$$\text{Specificity, SP} = \frac{\text{True negative}}{\text{Total number of negative subject}} \tag{7}$$

$$\text{Sensitivity,}\quad \text{SE} = \frac{\text{True positive}}{\text{Total number of positive subject}} \tag{8}$$

When we present the testing image of proposed regression-deep CNN, in the test image we highlight the normal, pre-cancerous as benign and post cancerous as malignant region and calculate the performance index. Table 2 shows the comparison of performance index for 100 training data sets.

In task 1: classification of malignant with benign tumors. The proposed regression-deep CNN achieved an accuracy of 91.4% and compare the result from expert oncologist.

In task 2: classification of malignant tumor and pre-cancerous tumor. For this we considered the three different classes of image with different stage. The regression-deep CNN model achieves 91.56% as compared with expert classification.

We validate our algorithm with other conventional classification algorithm namely SVM and DBN model. From SVM classifier the classification accuracy for task1 was 82.4% and for DBN 84.5% based on same data set. For task2 we obtain 85.5% for SVM and 87.2% for DBN for same data set. We compare proposed regression CNN with three partition class data onto expert oncologist classified image. The area under curve Fig. 6a with maximum of 1 is indicated.

The red dot in Fig. 6a shows the CNN classified value lies close to the experts predicted value. Where each red dot is represented sensitivity and specificity of expert data. The green lines in Fig. 6a show the average accuracy of proposed CNN for the different training data sets. In Fig. 6d, we increase the training image data onto 500 malignant image samples and for that we obtain an overall accuracy of 94.5% which is demonstrating proposed deep CNN algorithm is highly reliable when the training is increased compared to other computing techniques. Also, we compare Fig. 6a, b, c in terms of area under the curves with its performance index. The proposed partitioned deep CNN algorithms have higher value. This performance result is presented in Table 2 for 100 malignant training and Table 3 for 500 image patch training.

The data visualization of SVM, DBN and regression-based network algorithm is shown in Fig. 5. The data visualization for three classes partitioned by deep CNN of two dimensions is shown in Fig. 6. We cluster the different class by point color for differentiating three classifiers.

Conclusion

In this research paper, we design and developed a deep learning algorithm based on partitioned convolution neural network of automatic cancer diagnostic system. We present the examined feature of hyperspectral medical image of oral cancer case studies. Also, the examined features of hyperspectral image were presented visually by stochastic neighbor embedding method. We match the performance of designed deep CNN of other conventional classification techniques like SVM and DBN. Obtained accuracy by this regression-based partitioned algorithm was 94.5% with specificity 0.98 and sensitivity of 0.94 which is higher than another base classifier. Also, we show the increase in accuracy by 4.5% using large number of cancer subject data set for training phase to 500 image data sets was obtained. Hence, in this analysis the processing algorithm clearly predicted the tumor was cancerous tumor or benign. From the single phase of training this proposed deep CNN can provide accurate classification. Hence, this deep learning algorithm is easily deployed on simple workbench for

Table 2 Evaluation result comparison by SVM DBN and proposed regression-based partitioned deep learning CNN algorithm for 100 malignant image patch training

Classification method	Author, year	Accuracy	Specificity	Sensitivity
SVM	Deepak Kumar et al. (2018)	82.4	0.86	0.76
DBN	Dey et al. (2017)	84.5	0.89	0.82
Proposed CNN algorithm	Proposed method	91.4	0.94	0.91

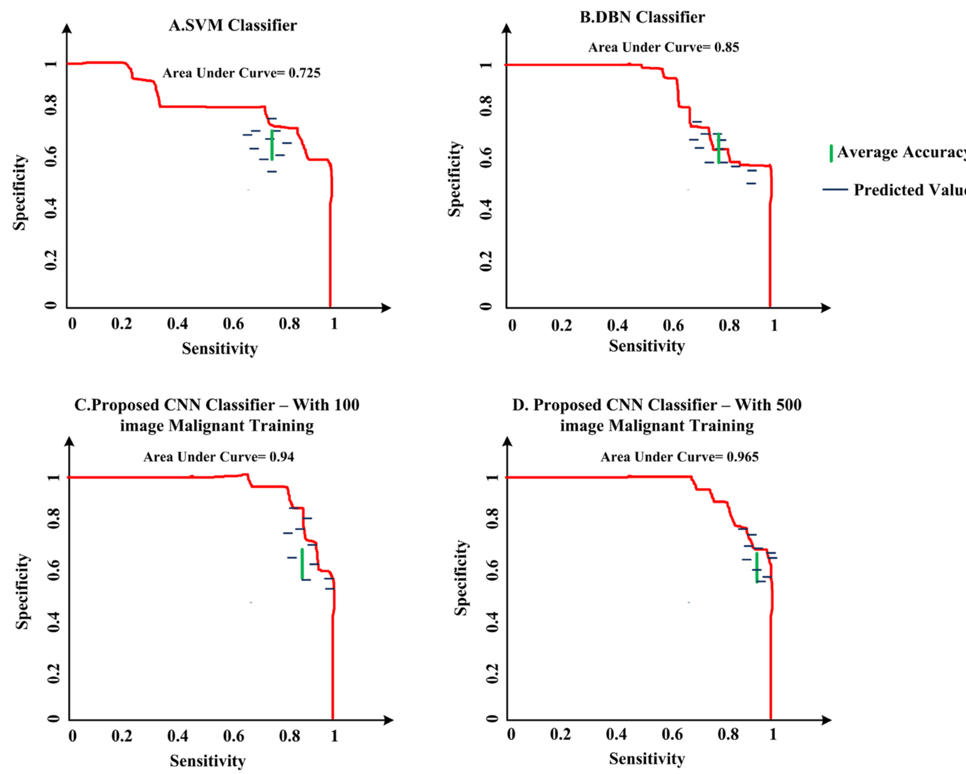

Fig. 6 Performance index comparison of HSI oral cancer classification by SVM, DBN with proposed regression-based deep CNN method algorithm

Table 3 Evaluation result comparison by SVM, DBN and proposed regression based partitioned deep learning CNN algorithm for 500 malignant image patch training

Classification method	Author, year	Accuracy	Specificity	Sensitivity
SVM	Deepak Kumar et al. (2018)	84.2	0.87	0.82
DBN	Dey et al. (2017)	86.7	0.91	0.84
Proposed CNN algorithm	Proposed method	94.5	0.98	0.94

providing an automatic medical image classifier without expert knowledge.

Acknowledgements The authors would like to thank the Department of Electrical Engineering, Indian Institute of Technology, Delhi and the Management, Principal of Mepco Schlenk Engineering College, Sivakasi for providing us the state-of-art facilities to carry out this research work.

Compliance with ethical standards

Conflict of interest The authors confirm that they have no conflict of interest regarding this research article.

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