Deep Learning Classification Method to Detect and Diagnose the Cancer Regions in Oral MRI Images

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Abstract

The paper proposes deep learning algorithm used to classify the oral images into either normal or abnormal images. The cancer regions are segmented using morphological operations. The segmented cancer regions are further diagnosed into 'Mild' or 'Severe' using deep learning algorithm. The main advantage of the deep learning algorithm is that it requires minimum number of oral images for both classification and diagnosis stages of the proposed work. In this paper, the total number of cancers affected oral images used is about 160 and the proposed oral cancer detection system using CNN classification approach classifies 159 cancer affected oral images correctly and achieves 99.3% of detection rate.

Keywords: *Deep learning, cancer, oral images, detection system, detection rate.*

Introduction

The term cancer, means "crab" in Latin, was coined by Hippocrates in the fifth century to describe a family of diseases. The tissues grow and spread unrestrained throughout the body, eventually choking of life. Cancer, in simple terms, is the disease caused by malfunctioning of cells, lost their control on proliferation. The cluster of cells, called a tumor or a neoplasm, constantly expands in size. Occasionally, cells might spread throughout the body, forming new tumors at distant sites, and the process of dissemination is called metastasis. Cancer, a multifactorial disorder, arises due to the defect in genetic makeup and exposure to environmental insult. Oral cancer, a life-threatening cancer worldwide, arises in the oral cavity due to ill-habits such as tobacco smoking and chewing. Cancer might occur anywhere in the body and a common strategy is to name them based on the organ or the type of cell they originate; the net result is more than 100 types of cancer. Among them, oral cancer is one of the most common malignancies present in the head and neck region.

Oral cancer, a malignant neoplasm of the mouth, is the fifth most frequent cancer in occurrence and eighth most common cause of cancer related deaths worldwide. The burden of oral cancer, worldwide, is drastically increasing despite of the advanced procedures available for early diagnosis and treatment. Oral cancer rates are rising in several countries dramatically. The mortality rate due to oral cancer worldwide is 30% and 12% in male and female respectively. Tobacco smoking and chewing are considered as the major predisposing factors for the development of oral cancer. All forms of tobacco habits are significantly associated with the development of oral cancer. Smokeless Tobacco (SLT) has been accepted as one of the strongest risk factors for the development of oral carcinoma.

In this paper, deep learning algorithm such as Convolutional Neural Networks (CNN) is used to classify the oral images into either normal or abnormal images. The cancer regions are segmented using morphological operations. The segmented cancer regions are further diagnosed into 'Mild' or 'Severe' using deep learning algorithm.

Literature Survey: A hybrid method was used by combining Fuzzy C-Means and neutrosophic algorithm for segmentation of tumors in the oral panoramic image proposed by Alsmadi (2016)[4]. It used speckle reduction by 3×3 size median filter to reduce the speckle noise, using neutrosophy algorithm. This approach provided a significant improvement in segmenting oral lesions. The accuracy comes from the use of indeterminacy degree to cluster the region and determination of the tumor. However, as this study was based on cluster calculation and image boundary location, shadow areas on the panoramic image will be a concern in terms of false detection. A study utilized variants of Support Vector Machine (SVM), such as Linear SVM, Quadratic SVM and Cubic SVM, were used to classify tumors on optical coherence tomography images. They compared the sensitivity, specificity and accuracy in six different classification conditions (Banerjee et al. 2016)[5]. Tanupriya Choudhury et al. (2016)[6] proposed the Intelligent Classification of Lung and Oral Cancer through diverse data mining algorithms. Logistic regression was a powerful tool modeling and also used for generalization of the linear regression. The optimal quantity of the Logic Boost iterations was performed and cross validated, taken to the selection of the attribute was automatic. Yi-Ying Wang et al. (2016)[7]presented a new color-based approach for automated segmentation and classification of tumor tissues from microscopic images. The procedure consists of a three-stage Color-Based Feature Extraction (CBFE) system. It normalized all the acquired images to the same color distribution by color transformation. Computerized selection of training samples was used for Automatic feature extraction. A similar study was made by Chang et al. (2016)[8] using hybrid feature extraction and machine learning classification algorithm with biomarkers. They proposed and tested five tumor classification method. The method, Adaptive Neuro Fuzzy Inference System (ANFIS), achieved the highest classification rate of 93.81% by combining the clinical pathologic dataset and biopsy images. This study considered patient's case as a whole. However, if the clinic pathologic dataset or images were considered as a separate sample, the result might not be achieved over 90% accuracy rate. In other words, the accuracy of the method rely on the patient's information.

An automated oral lesion detection method was studied by Galib et al. (2015)[2]. They discussed two systems to discover the two types of common lesions in the oral cavity. It achieved 92% sensitivity with 32% of false positives on average in close border lesions and 85% sensitivity with no false positives in open border lesions. Moreover, it had also discussed the possibility of improvement in open border lesion algorithm to 100% sensitivity with only 13% of false positives. Belvin Thomas et al. (2013)[3] proposed Texture Analysis Based Segmentation and Classification of Oral Cancer Lesions in Color Images using ANN. The objective was to select a reduced set of features that clearly distinguish between different groups of malignancy caused by carcinoma of different areas of oral cavity. They proposed the use of textural and run-length features of camera images. Hobdell et al. (2003)[1] investigated the relationship between socioeconomic status variables and oral health in an attempt to determine the association between social, economic and behavioral risk factors and the incidence of oral cancer among other oral health concerns. Their results described a marked gradient in oral diseases between the most highly and the least socio-economically developed countries and there was an apparent association between oral cancer and the socioeconomic status variables.

Proposed Methodology: In this paper, deep learning algorithm is used to classify the oral images into either normal or abnormal images. The cancer regions are then segmented using morphological operations. The segmented cancer regions are further diagnosed into 'Mild' or 'Severe' using deep learning algorithm. The main advantage of this deep learning algorithm is that it requires minimum number of oral images for both classification and diagnosis stages of the proposed work. Figure 1 shows the proposed oral cancer classification and diagnosis system using Convolutional Neural Network (CNN) classification approach.

Enhancement: In this paper, adaptive local histogram equalization framework is applied on the low-resolution oral MRI image for improving the intensity level of each pixel in the source image. In this section, the following steps are used to detect and remove the noisy pixels in oral MRI images.

Step 1: The source oral MRI image is divided into n*n non–overlapping sub blocks, where, n is the odd number value.

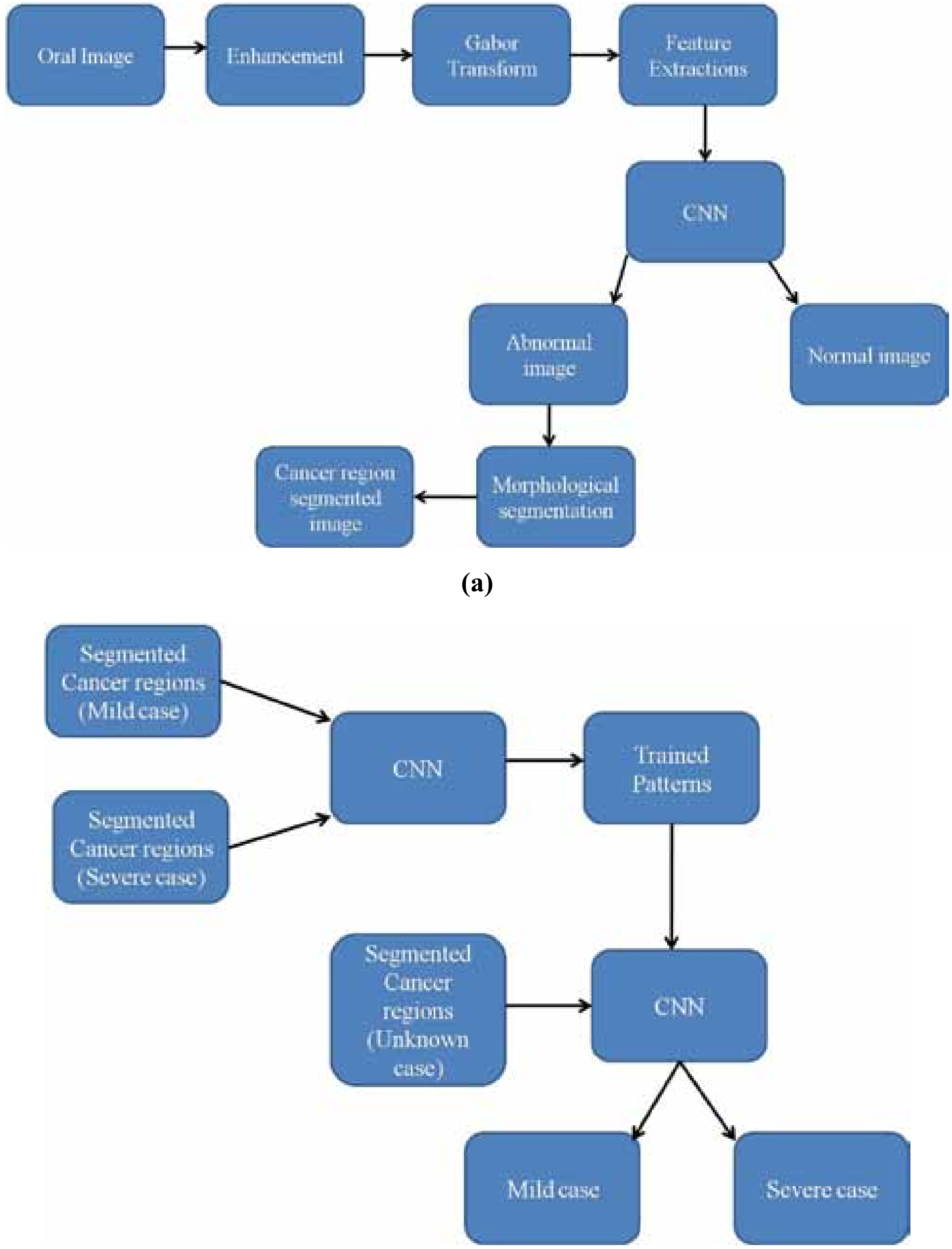
Step 2: In each n*n non–overlapping sub blocks, place the pixels in horizontal, vertical and two diagonal direction into P1, P2, P3 and P4 sets, respectively.

Step 3: Make order of pixels in P1, P2, P3 and P4 sets and eliminate the lower and higher order pixel from each set.

Step 4: Find standard deviation of each pixel set and find similarity index of each pixel.

Step 5: Consider the sub pixel set which has low value of standard deviation.

Step 6: Apply adaptive mean filter in the final sub pixel set in order to remove the noisy content.



(b)

Figure 1 Proposed oral cancer classification and diagnosis system using CNN classification approach (a) Classification method (b) Diagnosis method

Gabor Transform: In this paper, Gabor transform is used for spatial into multi oriented image conversion. The Gabor kernel is multiplied with enhanced oral image and the Gabor kernel is given as,

$$G(x,y) = e^{\frac{-(x'^2 + \gamma^2 y'^2)}{2 * \sigma^2}} * Cos\left(2 * \pi * f * \frac{x'}{\lambda} + \varphi\right)$$

where,
σ: Standard deviation.
γ: Spatial aspect factor is a constant set to 1.
λ: Spatial wavelength.

$$y' = -x * \sin \theta + y * \cos \theta$$

The frequency of the Gabor kernel is assigned by ‘f’ and it is shifted from 1 to 5 concerning spatial angle factor. Consequently, five quantities of Gabor kernels are created by duplicating the Gabor kernel with Oral picture concerning distinctive frequencies. These Gabor multiplied pictures comprises of real and imaginary terms. Further, Gabor magnitude image is built by choosing the maximum pixel value at each position in the Gabor multiplied pictures (Y(x,y)) utilizing the condition.

$$Y(x,y) = I(x,y) * G(x,y)$$

where,

$I(x,y)$: Oral image;

$G(x,y)$: Gabor kernel

$Y(x,y)$: Output response of the Gabor multiplication;

$$|Y(x,y) = \sqrt{Real(Y(x,y)^2 + Imaginary\ ((Y(x,y)^2}$$

Feature Extractions: It is one type of texture features used for classifying the various regions in a Gabor transformed magnitude image. It encodes one feature value for one pixel in a Gabor magnitude oral image. The 3*3 window is placed on the Gabor transformed oral image and it computes LBP (Local Binary Pattern) for each pixel using its surrounding pixels. The size of Gabor magnitude oral image and its extracted LBP images are same.

Classification: The machine learning algorithms for cancer region detection in oral images requires number of external features. These machine learning method are not suitable for further severity diagnosis process. In order to overcome such drawbacks the conventional machine learning method called deep learning method - Convolutional Neural Networks (CNN) is used in this work to detect and diagnose the cancer regions in oral images. As in machine learning algorithm, CNN also have both training and testing phases. During the training phase of the CNN classifier, the normal oral images and abnormal oral images are trained by the CNN producing the trained patterns. During the testing phase of the CNN classifier, the source oral image is tested with respect to the trained patterns. The response from this CNN classifier is either normal or abnormal. The CNN architecture used in this research work is depicted in Figure 5.

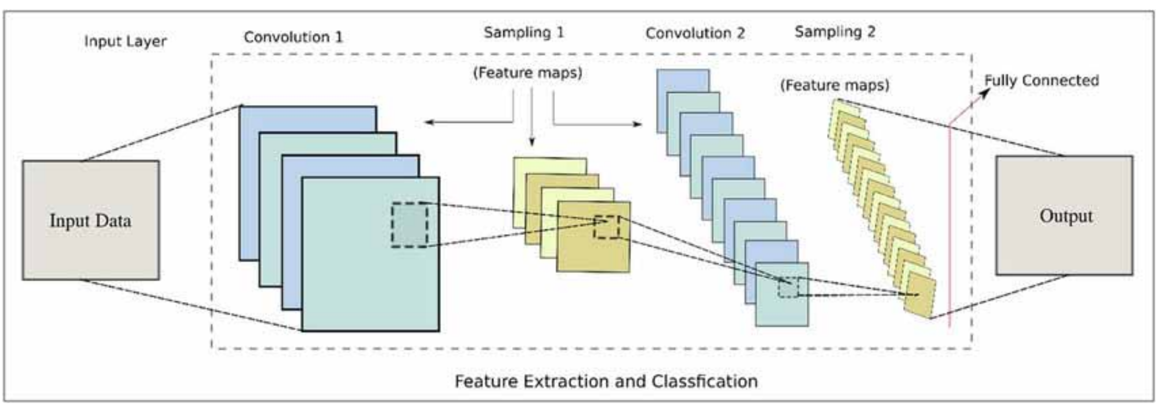


Figure 5 CNN architecture

The CNN architecture includes Convolutional layers, pooling layers, and fully connected layers. The Convolutional layer consists of a number of convolution kernels, which is a two-dimensional matrix of weights W. The convolution kernel convolves an input image (also a two-dimensional matrix) in the form of a sliding window with a matrix called feature map is obtained. Each Convolutional layer has Convolutional kernel itself and it is convolved with the oral image. The pooling layer is also called the sampling layer, uses the sliding window to convolve the input or the feature map so that it might reduce the feature dimension and the amount of calculation. Polling layer has two different types as “Average” and “maximum” pooling. Different from the Convolutional layer, the pooled layer (maximum pooling is adopted in this paper) does not depend on weights and parameters. In general, each feature map of the input is pooled in the same way and the number of features of the original input remains unchanged. Then, the fully connected layer is used to map the feature representations from the Convolutional layer to the sample space in order for classification, composed of a group of neurons and connections with weighted values. Since the number of the parameters of the fully connected layers is very large, some networks use the Convolutional neural networks to take place in the fully connected layers. The proposed CNN method for oral cancer image detection and classification is depicted in the following algorithm.

Input: Oral image;

Output: Classification response;

Start;

Step 1: The input oral image is convolved with kernel of first Convolutional layer and the response is produced.

Step 2: The size of the convolved sequences are reduced by passing these values through the pooling layer 1.

Step 3: The size reduced sequences are now passed through the Convolutional layer 2.

Step 4: The response from the second Convolutional layer is passed through the second pooling layer.

Step 5: The output response from the second Convolutional layer is feed into neural network architecture to produce the classification pattern.

End;

Further, mathematical morphological operations are used to segment the cancer regions in classified oral images. The morphological parameters such as area, width and height are computed for its diagnostic process. The segmented oral cancer regions are analyzed for the mild and severity of the cancerous regions using CNN classification.

Results and Discussions

The proposed fully automated oral cancer detection and diagnosis system is divided into two different sections as cancer region detection or segmentation and cancer region diagnosis. This automated cancer region detection and segmentation approach on oral images is applied on the oral images obtained from the open access dataset. The performance of the proposed oral cancer region segmentation on oral images using classification method is evaluated in terms of sensitivity, specificity and accuracy. These performance evaluation metrics are given in the following equations.

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$Accuracy\ (Acc) = \frac{TP + TN}{TP + TN + FP + FN}$$

The number of correctly detected cancer pixels in the classified abnormal oral image is noted by True Positive (TP), the number of correctly detected non-cancer pixels in the classified abnormal oral image are noted by True Negative (TN). The number of incorrectly detected cancer pixels in the classified abnormal oral image is noted by False Positive (FP), the number of incorrectly detected non- cancer pixels in the classified abnormal oral image are noted by False Negative (FN).

Table 1 shows the performance evaluation of oral cancer detection and segmentation using CNN classification method and it achieves 98.6% of sensitivity, 99.1% of specificity and 99.7% of oral cancer segmentation accuracy.

Table 1 Performance evaluation of oral cancer segmentation using CNN classification methodology

Parameters	Simulation results (%)
Sensitivity	98.6
Specificity	99.1
Accuracy	99.7

Table 2 shows the analysis of data augmentation method in CNN architecture on proposed oral cancer detection and segmentation.

Table 2 Analysis of data augmentation method in CNN architecture on proposed oral cancer detection and segmentation

Performance parameters	With Data Augmentation	Without Data Augmentation
Se (%)	98.6	93.7
Sp (%)	99.1	94.1
Acc (%)	99.7	95.6

Table 3 shows the comparisons of proposed oral cancer segmentation with various method. The proposed oral cancer detection system using CNN classification approach achieves 99.3% of detection rate, whereas Muzakkir Ahmed et al. (2017) achieved 90.1% of detection rate, Anuradha et al. (2015) achieved 89.5% of detection rate and Konstantinos et al. (2012) achieved 87.9% of detection rate.

Table 3 Comparisons of proposed oral cancer segmentation with other method

Authors	Methodologies	Detection Rate (%)
Proposed work	CNN classifier	99.3
Muzakkir Ahmed et al. (2017)	Thresholding technique	90.1
Anuradha et al. (2015)	Watershed segmentation algorithm	89.5
Konstantinos et al. (2012)	Decision Support System	87.9

Table 4 shows the comparisons of proposed oral cancer diagnosis system with other method. The total number of mild case oral images used in this work is 100 and the total number of severe case oral images used in this work is 150 as illustrated in Table 4. This proposed diagnosis method using CNN classification method classified 100 mild images as mild case category and the proposed method classified 150 severe case images as severe case category (99.3%).

Table 4 Comparisons of proposed oral cancer diagnosis system with other method

Authors	Number of Mild case images tested	Number of Mild case images correctly classified	Number of Severe case images tested	Number of Severe case images correctly classified
Proposed work	100	99	150	150
Zeeba Shamim Jairajpuri et al. (2019)	100	96	150	147
Muzakkir Ahmed et al. (2017)	100	72	150	142
Anuradha et al. (2015)	100	84	150	139
Konstantinos et al. (2012)	100	71	150	135

Conclusions

This paper develops a methodology using deep learning algorithm to classify the oral images into either normal or abnormal images. The cancer regions are segmented using morphological operations. The segmented cancer regions are further diagnosed into 'Mild' or 'Severe' using deep learning algorithm. The main advantage of this deep learning algorithm is that it requires minimum number of oral images for both classification and diagnosis stages of the proposed work. In this paper, the total number of cancers affected oral images used is about 160 and the proposed oral cancer detection system using CNN classification approach correctly classifies 159 cancer affected oral images correctly and achieves 99.6% of detection rate.

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