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Histological Grading of Oral Tumors using Fuzzy Cognitive Map

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ABSTRACT

Oral Tumor grading can be performed in many ways. To find the depth of the tumor, the conventional TNM (Tumor, Node, Metastatis) staging has been performed by experts for several years. But this staging system is not adequate for optimal prognostication and must be supplemented by different recent methods. This study uses Fuzzy Cognitive Maps (FCM) to grade oral tumors. Eight histopathological features were used to develop Fuzzy Cognitive Map model. Active Hebbian Learning (AHL), the supervised learning algorithm is used to train and improve the FCM's grading. 123 cases containing 85 normal and 38 abnormal cases of oral tumor were used for testing. The proposed model (FCM and AHL) achieved an accuracy of 90.58% for oral tumors of low grade and 89.47% of high grade.

Keywords: Oral Tumor, TNM, Fuzzy Cognitive Map, Supervised Learning, Active Hebbian Learning.

INTRODUCTION

Many attempts have been made to improve the diagnostic accuracy of the oral tumor characterization by using various types of Computer aided Technologies. Several experiments were conducted by the researchers for the classification of the tumor as benign or malignant[1]. Techniques like Dental X – Rays, Positron Emission Tomography (PET), Computed Tomography (CT), Biopsy and Magnetic Resonance Imaging (MRI) are used to test the presence/absence of Tumor. Classification of tumors is an important aspect for its respective diagnosis. However, the presence of cancer can only be detected through the process of biopsy. Among all other cancers, oral cancer has the highest death rate and has witnessed no improvements over the past 40 years. World health organization (WHO) suggested a grading system for the classification of tumors. According to WHO, tumors are classified into low – grade tumors and high grade tumors. In low grade tumors, there is no invasion of tissues or metastasis and there may be less risk of further progression. However, high grade tumors are characterized by a much higher risk of progression. Premalignant tumors may progress into cancer. The correct accuracy of the diagnosis depends on the expert's experience and knowledge. Several histopathological features were reviewed by various researchers for cancer classification[2,3]. Experts

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combine the features to determine the final grade of tumor. In this work, histopathological features such as Differentiation, Nuclear polymorphism, Mitoses, Stroma, Mode, Stage, Vascular and Inflammatory response were taken. The proposed method is based on FCM with the implementation of Active Hebbian Learning algorithm which improves the classification accuracy of FCM.

This paper is structured as follows: Section 2 presents the related literature study. Section 3 and 4 describes the methodology of FCM and AHL respectively. The development of FCM model for grading tumors is shown in section 4. Section 5 presents the experimental results and conclusion is shown in section 6.

Literature study

Classification and grading of cancers have been always been an epic area of interest for researchers. Muthu Rama Krishnan et al.,proposed a wavelet based texture classification for oral histopathological sections. As the conventional method involves in stain intensity, inter and intra observer variations leading to higher misclassification error, a new method is proposed. The proposed method, involves feature extraction using wavelet transform, feature selection using Kullback – Leibler (KL)[4].

Anuradha. K and Sankaranarayanan.K (2013) classified oral cancers using Feature Extraction Techniques. Dental radiographs were taken as input images. The tumor area is segmented using Watershed algorithm. Gray Level Co-occurrence Matrix (GLCM), Gray Level Run Length Matrix and Intensity Histogram feature extraction methods were used to extract features from the segmented image. Further, a supervised classifier, Support Vector Machine is used to classify the features as benign or malignant. Among the feature extraction methods, GLCM with SVM classifier achieved an accuracy of 96%[5].

Few researchers used Fuzzy Cognitive Maps to stage cancers.

Papageorgiou. E. I et al (2003) developed a FCM model to grade Urinary Bladder Tumors using Unsupervised Hebbian Algorithm. Eight Concepts were considered for grading. The classification accuracy was 93.18% for low grade tumors and 90.59% for high grade tumors[6].

Roopa Chandrika et al.,(2016) used Fuzzy Cognitive maps for grading breast tumors from Digital Mammograms. The textural features were obtained using Gray Level Co-occurrence Matrix (GLCM) and Laws Energy. These textural values are fed as input to Fuzzy Cognitive Map to classify the severity of abnormality present in digital mammograms[7].

Thuthi Sarabai and Arthi.K (2016) improved Fuzzy Cognitive Map with Cat Swarm Optimization Algorithm to classify breast cancers. GLCM features were extracted from the input preprocessed image. The performance of the system is evaluated with Mean Square Error, Sensitivity and Specificity[8].

MATERIALS AND METHODS

123 cases of oral tumor patients with the age groups 21 to 67 were collected. 85 are normal

Table 1: FCM grading for Oral Tumor

Concept	Histological Feature	Possible Assessment (Tumor scores)
C1	Differentiation	Much keratin, Some keratin, Squamous, Anaplastic
C2	Nuclear polymorphism	Few aniso, Moderate aniso, Many aniso, Bizarre
C3	Mitoses	Occasional, Few, Moderate, Many
C4	Stroma	Abundant, Dense, Delicate, None
C5	Mode	Pushing, Bands, Cords, Diffuse
C6	Stage	No invasion, Microinvasion, In connective tissue, Deep
C7	Vascular	None, Possible, Few, Many
C8	Inflammatory response	Marked, Moderate, Slight, None
C9	Degree of Tumor grade	Low, high

cases and 38 are abnormal cases.

Fuzzy Cognitive Map

Fuzzy Cognitive Map was first enhanced by Kosko. B[9]. These are fuzzy – graph structures which represents causal reasoning. The proposed work used Fuzzy Cognitive Maps with Active Hebbian Learning. A Fuzzy Cognitive Map integrates the accumulated experience and knowledge on the causal relationship between factors/ characteristics/ components of any system; due to the way it is constructed, i.e., using human experts who know the system and its behaviour under different circumstances[10]. It is one of the unsupervised learning algorithms which classify data by using concepts. Weights are calculated between the concepts. The value of the weight indicates the strong influence between concepts. The value calculated between the interconnection of concepts lies between 0 and 1. The Fuzzy Cognitive Map represents knowledge and relates states, processes and inputs. When compared with neural networks, it is relatively easy to represent knowledge. The sample FCM is shown in Fig 1.

The w indicates how strongly C1 influences C2. If w >0, there exists a positive causality between C1 and C2. i.e., An increase in C1 will also cause to increase C2. Negative causality is present if w < 0. If there is a decrease in C1, there will be a decrease in C2 also.

Here, in this work, the FCM model is constructed using eight concepts shown in Table 1.

Development of FCM

123 cases of oral tumor patients with the age groups 21 to 67 were collected. Using various diagnostic tools available today, experts diagnosed 85 as normal cases and 38 as abnormal cases. The abnormal cases were mostly Squamous cell carcinoma in the neck regions and the normal cases were mostly Lichen Planus. To construct a FCM, eight histopathological criteria (Table 1) were used.

Table 2: Comparison of FCM Grading Model with other Techniques

Normal/ Abnormal cases	TNM + Biopsy	FCM Grading tool
Normal cases (85)	85	77
Abnormal cases (38)	38	34
Accuracy % for low grade tumor	100	90.58%
Accuracy % for high grade tumor	100	89.47%

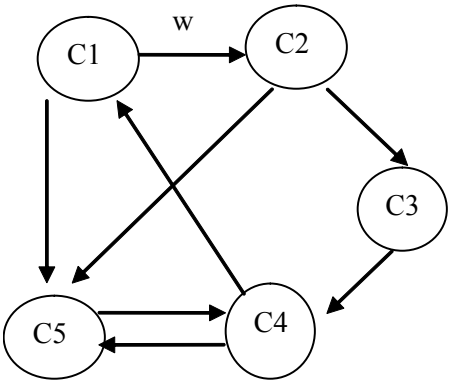

Fig.1: Sample FCM structure

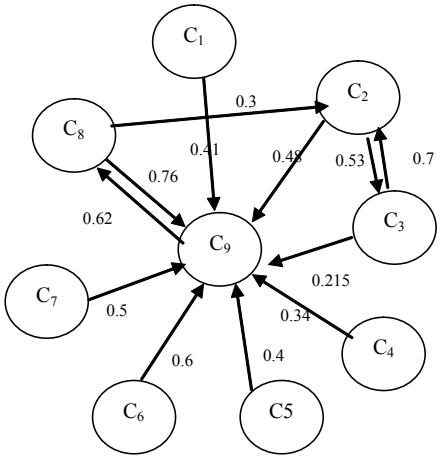

Fig.2: FCM model for oral tumor grading

Different grading systems were reviewed in [2]. As the database contains more cases of Squamous Cell Carcinoma, Fisher classification is used. Each criteria contains 2 - 5 possible values. These possible values are the factors of the grading system.

The initial process is to decide the number of concepts and the relation between them. These concepts encode the level of malignancy. As these concepts are interrelated to one another, the dependency matrix can be easily developed by using FCM map.

The FCM grading model was developed using the eight concepts (C1 to C8): The eight concepts represents the eight variable of the tumor grading system. The Ninth concept (C9) represents the degree of tumor grade. Concept C1 represents the differentiation, C2 represents Nuclear polymorphism, C3 represents Mitoses, C4 represents Stoma, C5 represents Mode, C6 represents Stage, C7 represents Vascular and C8 represents Inflammatory response. The ninth concept represents the degree of tumor grade. All the values are in the interval (0, 1). The threshold (0.5) decides which event is stimulated.

The fuzzy rule for each interconnection was evaluated using Fuzzy reasoning and from that fuzzy weights (Equation 1) are defuzzified. A fuzzy set is modelled {positive very high, positive high, positive medium, positive weak, Zero, negative weak, negative medium, negative low and negative very low} by using the degree of influence of concepts. These fuzzified values are converted into numerical values using defuzzification method.

The degree of influence among the concepts was presented using IF – THEN conditions. IF a small change occurs in the value of Concept$_i$, then a small change is caused in the value with Concept$_j$

Consider for example, the value X_i of the Concept C_i influences the Concept$_j$

The value A_j for each concept C_j is calculated using the following equation:

$$A_j^{(t+1)} = f\left(A_j^{(t)} + \sum W_{ij} . A_i^{(t)}\right) \quad ...(1)$$

Where,

$A_j^{(t+1)}$ is value of concept C_j at step t+1,

$A_i^{(t)}$ is the value of concept C_i at step t, and W_{ij} is the weight of the arc from Concept C_i towards concept C_j and *f* is a threshold function.

Active Hebbian Learning:

Classification rate and efficiency of the FCM can be enhanced by applying Active Hebbian Learning (AHL). AHL is an unsupervised learning algorithm[11,12]. This will regulate the weights of the FCM. The main advantage of AHL is that it is based on asynchronous decision making process similar to human decision skills and it can decide new FCM causal links between all the Concepts. This algorithm takes the input values of concepts which will strengthen and weaken the FCM causal links between the concepts. Due to this classification capability is increased.

Evaluation of oral cancer cases were done after the development of FCM and the implementation of AHL. For each and every case, the values are calculated in the interval [0-1]. The grading system with the new weighted interconnections among concepts was calculated. After few interactions, the C9 for every case is calculated.

DISCUSSIONS AND RESULTS

The performance of FCM grading system is evaluated. This tool achieved an accuracy of 90.58% (77/85) for oral tumors of low grade and 89.47% (34/38) of high grade. From Fig 2, it is observed that the value (0.76) for Inflammatory response (C_8) is

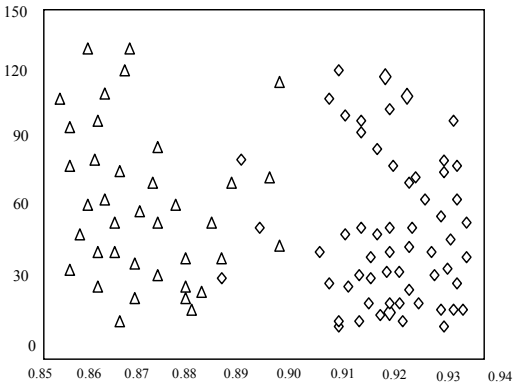

Fig. 3: Estimated grade values

more important to find the degree of grading. The graph plotted (Fig 3), shows the final grade values of C_9 for each of 123 cases.

The horizontal axis (X) represents the calculated values of the Grade improved using AHL algorithm and the vertical axis (Y) represents the number of cases used for each grade category.

The symbol ∆[* Internal error: Invalid file format. | In-line.WMF *]' represents the estimated "Grade values" for low grade tumor and ∆[* Internal error: Invalid file format. | In-line.WMF *]' for high grade respectively. For most of the cases, the values are distinct, which makes the classification easier.

To define the decision region for each case, the mean value m1 and m2 for each category is estimated.

The decision boundary was determined as the perpendicular bisector of the line joining m1 and m2. So the threshold is estimated as 0.92 for each grade category. The values lower the 0.92 are low grade (normal) and those values which are higher than 0.92 are high grade (abnormal). This procedure was repeated for many times. The average success rate has achieved.

The Table 2 shows the comparison of results for TNM grading and FCM grading:

CONCLUSION

Researchers mainly focus on microscopic procedures to grade the tumor. And in many cases, the accuracy obtains only at the advanced stage where treatment becomes unsuccessful. The TNM system does not provide information on the biological characteristics. So a reliable method for categorization with excellent accuracy is essential. The proposed method used FCM grading model to categorize the tumor cases into low grade and high grade. Further, to improve the values, Active Hebbian Learning algorithm was used. The classification rate obtained was 90.48% and 89.47% for low grade and high grade respectively.

In future, features can be extracted using the feature extraction methods and can be given as input to the FCM.

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