RESEARCH ARTICLE

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Oral Cancer Prediction Using a Probability Neural Network (PNN)

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Abstract

Objective: In India, usually, oral cancer is mostly identified at a progressive stage of malignancy. Hence, we are motivated to identify oral cancer in its early stages, which helps to increase the lifetime of the patient, but this early detection is also more challenging. **Methods:** The proposed research work uses a probabilistic neural network (PNN) for the prediction of oral malignancy. The recommended work uses PNN along with the discrete wavelet transform to predict the cancer cells accurately. The classification accuracy of the PNN model is 80%, and hence this technique is best for the prediction of oral cancer. **Results:** Due to heterogeneity in the appearance of oral lesions, it is difficult to identify the cancer region. This research work explores the different computer vision techniques that help in the prediction of oral cancer. **Conclusion:** Oral screening is important in making a decision about oral lesions and also in avoiding delayed referrals, which reduces mortality rates.

Keywords: Oral cancer- Discrete wavelet Transform (DWT)- Probabilistic Neural Network (PNN)- malignancy

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Introduction

In recent days, across the world, oral cancer is one of the most affected kinds of head and neck cancer, which leads to 177,757 deaths each year. The survival rate has increased from 75 to 90 percent when it is identified by early diagnosis, so that the oral cancers must be detected at an early stage. This is due to the delays in recommendations to oral cancer experts and the lack of knowledge on oral cancer signs. The uncontrollable development of cells that attack and affect the surrounding tissue The tongue, the tissue lining the mouth and gums, beneath the tongue, at the base of the tongue, and the area of the throat at the posterior of the mouth are all places where oral cancer originates. After the age of 40, men are more likely than women to develop oral cancer. Oral cancer is affected by tobacco use, alcohol usage (or both), or infection with the human papillomavirus (HPV). It is called a squamous cell carcinoma (OSCC), since in the dental region 90% of cancers start in squamous cells. Most of the oral cancer cases are detected at a progressive stage, which leads to high mortality. To increase the life span of the patient, the researcher needs to implement early diagnosis of oral cancer. Due to the heterogeneity in the appearance of oral lesions, it is difficult to identify the cancer region. This research work explores different computer vision techniques that help in the prediction of oral cancer. Oral screening plays an important role in making decisions on oral lesions and also helps to avoid delayed referrals and reduce the mortality rate.

Related work

The following survey discusses the various techniques used for early oral cancer detection.

1- The survival rate of the patient can be improved with the help of oral cancer screening, which leads to an early diagnosis. But, still, a biopsy is an invasive and painful method. The proposed work uses fluorescence visualization using an optical instrument. It is one of the non-invasive techniques that provide results in real time, and investigations can be repeated. Fluorescence imaging technology was evaluated using subjective and objective evaluations.

2- Recent analysis of artificial technology shows that it has been mostly used in our daily lives and has been used in healthcare, medical science, agriculture, etc. As a part of AI, many machine learning techniques were used in medical findings and treatments using emerging medical imaging methods. The research work will perform an extensive survey of machine learning in dental, oral, and craniofacial imaging.

3- The research work recommended a fast, cost-effective

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deep learning method to identify oral cavity squamous cell carcinoma patients using photographic images. The recommended method uses deep learning algorithms, such as cascaded convolutional neural networks, to identify OCSCC from photographic images.

4- The research paper developed a state-of-the art infrastructure approach that helps to categorize oral cancer using hyperspectral imaging. It is a noninvasive method for the classification of cancer. An accuracy of 94.75 percent has been obtained by deep Boltzmann machine (DBM) and SVM classification in hyperspectral images.

5- The recommended research article enhances the accuracy of tumor identification in the oral cavity. The research work uses CT image pre-processing, and the segmentation was done through fuzzy C-means. The accuracy of 90.11% was obtained by the proposed research using an anisotropic filter along with a fuzzy C-means algorithm.

6- Oral squamous cell carcinoma (OSCC) is a type of cancer of the oral epithelium. This OSCC-S type of cancer is diagnosed at a late stage; hence, the research article proposes an effective screening method for early diagnosis of OSCC, which in turn helps to improve the patient's lifetime. The author recommended using deep learning technology on CLE images to perform automatic diagnosis of OSC. The recommended method provides an advantage of 88.3% over the textural feature-based machine learning technologies.

7- The survival rate of the patient is increased to 75–90% when the oral cancer is identified at an early stage. The research work uses a second-stage classifier network to classify the recognized area into three categories (benign, OPMD, and carcinoma).

8- VELSCOPE is one of the oral screening devices that uses autofluorescence. The device provides inconsistent results when utilized to discriminate between normal, premalignant, and malignant lesions. Hence, the author uses a quadrature discriminant analysis (QDA) classifier and a linear discriminant analysis (LDA) classifier for autofluorescence images.

9- The main objective of this research is to implement automatic identification of OSCC by artificial intelligence techniques. Morphological and textural features are studied from microscopic biopsy images of OSCC. The research work uses five classifiers, namely: support vector machines, logistic regression, linear discriminant, K-nearest neighbors, and decision trees. Among all decision tree classifiers, this one provides 99.78% accuracy.

10- The author discussed the basic reasons for the occurrence of oral cancer and also addressed the fundamental concepts of epidemiological aspects addressing carcinogenesis and oral potentially malignant disorders. Further risk factors involved and future challenges in the detection of oral cancer were also reviewed.

11- The author implemented a novel approach to deep neural networks that were used to automate the detection of oral cancer in order to handle the difficult task. Further, the system is automated with the support of deep neural networks. The research work was carried out by two deep learning-based computer vision approaches in order to automate the recognition and classification of oral lesions.

12- The author introduced vision-based adjunctive technologies that help identify oral potentially malignant disorders (OPMDs); this article proposes potential applications of computer vision methods in the field of oral cancer screeningeening. By exploring the recent techniques in deep learning, a two-stage model was utilized to classify the oral lesion and categorize the abnormal area into three categories (benign, OPMD, and carcinoma) with a second-stage classifier network. The recommended method offers a great and low-invasive tool that helps improve the detection of OPMD.

13- The prior detection of oral cancer is poor since 50% of patients are diagnosed at an advanced stage. Hence, there is a need to implement a rapid, noninvasive, and cost-effective deep learning approach to locate oral cavity squamous cell carcinoma (OCSCC) patients with the help of photographic images. This research work is automated with the help of a deep learning algorithm. The oral cavity squamous cells are detected from the photographic image using cascaded convolutional neural networks.

14- Saliva is one of the most effective noninvasive early-stage detections of oral cancer, with high sensitivity and specificity. The recommended method explores the imaging biomarker to analyze spectroscopic characterization of saliva in oral potentially malignant disorders (OPMDS), and OC is broadly considered. The research work uses multifractal-based methodology in order to analyze the alteration of the salivary fern pattern in various OPMDS.

15- Anatomically, there is a close relationship between the oral cavity and the central nervous system. 30–40% of sensory and motor nerves are located on the mouth and face. The dental surgeon has the responsibility to diagnose the orofacial manifestations of neurological disorders. As a result, familiarizing the dental surgeon with these manifestations is critical for better identification, analysis, and accurate decisions when treating their related Neurological Disorders. It is necessary to implement the novel approach to assist the dental surgeon with an early diagnosis of neurological disorders and all kinds of rehabilitative treatments. The hybrid optimized method provides an accuracy of 98.3% when compared with other methods.

16- Early detection of oral lesions will help patients with oral cancer live longer lives.The research OCT is one of the minimally invasive tomographic imaging technologies utilized to detect changes in premalignant or malignant oral mucosa.

17- This paper implemented an algorithm for 3DCNNs-based image processing to identify oral cancer in its earlier stages. The 3D and 2D CNNs were designed using hierarchical structure, which helps classify the oral tumors as benign or malignant. The research work utilizes the CT oral images to extract the spatial features and spatial dynamics extracted from 3DCNs. It provides higher accuracy than the 2D CNNs.

Materials and Methods

The suggested work uses the discrete wavelet transform to extract the features in the frequency domain. A probabilistic neural network helps classify oral cancer as benign or malignant.

The flow diagram (Figure 1) represents the various phases involved in the oral cancer classification.

It has six phases. The first phase is the collection or generation of databases. The second phase involves pre-processing. Next phase: segmentation of lesions from the input image. In phase 4, feature extraction is performed, and in order to classify the lesion portion, statistical analysis is performed in phase 5. Finally, the labeling of cells is done in phase 6.

Pre-processing 1

The pre-processing is applied to the database in order to eliminate the artifacts that will impact the result. During pre-processing, the original RGB image is converted into various different components described by the following mathematical function:

Cyan (C) = (G+B)
Magenta (M)= (R+B)
Yellow (Y) = (R+G)
Hue (H) is obtained by using the following function
Num = (R-G) +(R-B) / 2
Den= √((R-G)2+(R-B)(G))
$\theta=\cos^{-1}$(num/den)
H= { θ if B≤ G
360- θ if B> G
Saturation (S) was achieved by using calculation
Num = min (min (R, G), B)
Den =R+G+B
S= 1- (3*num)/den
Intensity (I) was got as follows
I=(R+G+B)/3

Finally, HIS was calculated as HIS= cat (3, H, S, I), that is, combination of the components.

Discrete Wavelet Transform 1.1

Both the time and frequency domains are integrated in the wavelet transform. It generates high-pass and low-pass signals by passing them through high-pass and low-pass filters. Low-pass filtering generates the LL and HL regions, and this high-pass signal is further decomposed into the HL and HH regions. Until we get the desired portion from signals, this process is continued. Daubechies wavelets decompose the wavelets into subbands (LL, LH, HL, and HH). The approximate and detailed coefficients of the input image were obtained at the end of decomposition. The Daubechies wavelet function is represented by the following equation:

f(db)= (aL| d L)
aL= (a1, a2 ……… a N/2)
bL= b1, b2 ……… b N/2)
Where a- approximation sub band
d – detailed co-efficient

The recommended method uses DWT, which has the ability to differentiate between normal and abnormal cases of various cancers. The data elements of DWT are separated by various or multiple frequency components. The wavelet transform works along with the function called "mother wavelets," like Haar, Daubechies, Mexican Hat, Morlet, etc. This paper uses Daubechies wavelet transform to perform decomposition. The wavelet families are derived from mother wavelets.

Gray Level co-occurrence Matrix 1.3

(GLCM) techniques help separate second-order statistical texture features. A few GLCM features are listed as follows.

Feature Extraction 1.4

Following are the list of features extracted using GLCM.

Entropy: It is defined as the uncertainty of the textural image.

$$h = -\sum_{k=0}^{L-1} p_{lk} p_{lk}) \tag{1}$$

p lk = probability of the K th level

Energy: It is defined as the measure of the amount of degree of recurrence of a pixel pair. Energy is the parameter that is used to measure the similarity of an image.

$$E = \sum_{i,j} P(i,j)^2 \tag{2}$$

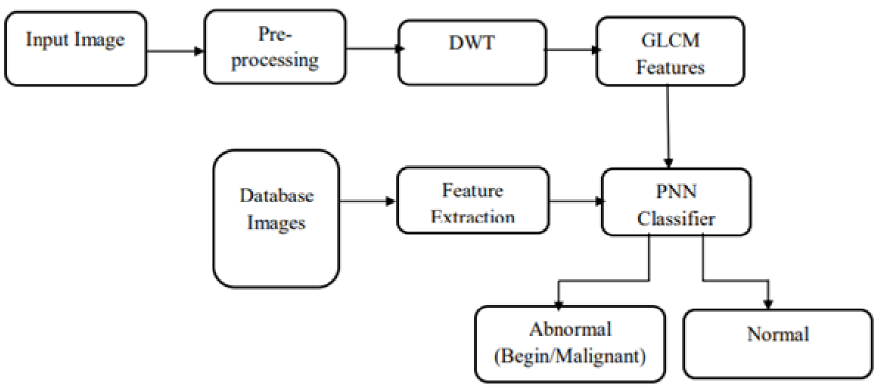


Figure 1. Classification Flow Diagram

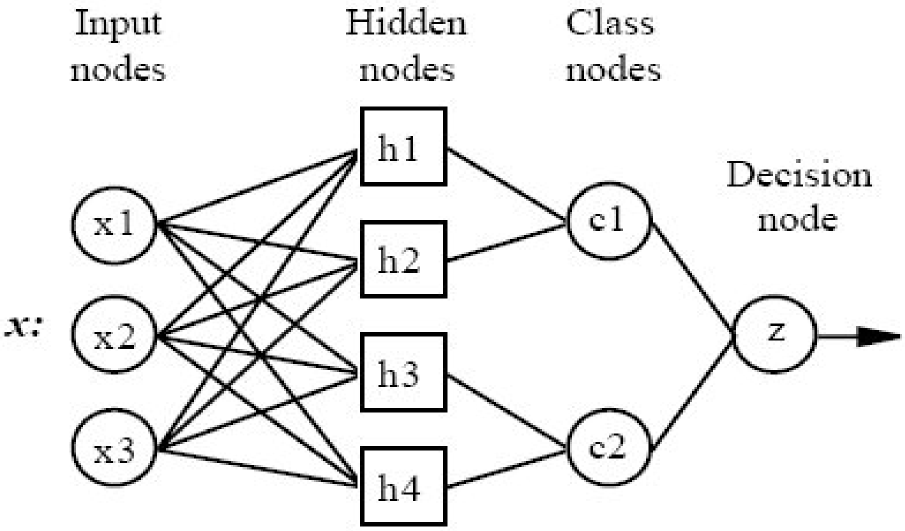


Figure 2. PNN Network

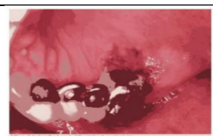
	Input Image	Gray scale image	Predicted image
Verrucous carcinoma			
squamous cell carcinoma			
Squamous cell carcinoma			

Figure 3. Depicts the Different Types of Oral Cancer Input Image, Gray-Scale Image, and Its Predicted Image Using a PNN Classifier

Contrast:

For an image, the intensity difference between the pixel and its neighboring pixels is called the contrast.

$$C = |i - j|^2 p(i,j) \quad (3)$$

Correlation: In a whole image, a pixel that is correlated with the neighborhood is called a “pixel.” The range lies between -1 and 1. The value is 1 for the positively correlated image and -1 for the negatively correlated image.

$$\text{corr} = \sum \frac{(i-\mu_i)(j-\mu_j)(p(i,j))}{\sigma_i \sigma_j} \quad (4)$$

µi, µj - Mean, σi,σj, Standard deviation

Pi, Pj- Partial probability function

Probabilistic neural network (PNN)

A probabilistic neural network (PNN) helps to achieve classification and pattern recognition in feed-forward networks. The parent probability distribution function (PDF) of each class is approximated by a Parzen window and a non-parametric function. Utilizing the PDF of each class, estimate the probability of new input data. To assign the class with the maximum posterior probability to new input data, the 33 Bayes ‘rule is then utilized. By doing so, we reduced the probability of misclassification. In a PNN, the processes are systematized into a multi-layered feed-forward network with four layers:

- Input layer
- Hidden layer
- Pattern layer/Summation layer
- Output layer

Figure 2. PNN Network

Once input is provided to the input layer, the distance from the input vector to the training input vector is calculated. The second layer sums the involvement for every class of inputs and creates its final output as a vector of probabilities. It produces a 1 (positive identification) for that class and a 0 (negative identification) for non-targeted classes.

Advantages

- Outliers are mostly unnoticed by PNN networks.
- PNN has the potential to be more accurate.
- The target probability scores were predicted with high accuracy using PNN.
- PNNs are approaching Bayesian optimal classification.
- It accurately segments the cancer regions from the image.
- Classifying the cancer detection images for accurate detection
- Cancer will be recognized at an early stage.

Results

The following Figure 3 depicts the different types of oral cancer input image, gray-scale image, and its predicted image using a PNN classifier. Comparing with the conventional types, the recommended PNN provides good accuracy.

Discussion

In this research, we employed a probabilistic neural network with a discrete wavelet transform to diagnose disease early, identify the type of oral cancer, and determine the patient's survivability. The proposed strategy aids in improving the accuracy of diagnosis as well as the efficacy of treatment. The probabilistic neural network has the highest classification accuracy, specificity, and sensitivity, as well as the best results in terms of geometric mean sensitivity and specificity, making it a robust model.

Author Contribution Statement

All authors contributed equally in this study.

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Conflict of Interest

Author declares no conflict of interest.

References

Aubreville M, Knipfer C, Oetter N, et al (2017).Automatic Classifcation of Cancerous Tissue in Laserendomicroscopy Images of the Oral Cavity using Deep Learning. *Sci Rep*, **7**.

César Rivera (2015). Essentials of oral cancer. *Int J Clin Exp Pathol*, **8**, 11884-94.

Fua Q, Chen Y, Li Z, et al (2020). A deep learning algorithm for detection of oral cavity squamous cell carcinoma from photographic images: A retrospective study. *E Clin Med*, **27**, 1-7.

Hashem M, Vellappally S, Fouad H, Luqman M, Youssef A (2020). Predicting Neurological Disorders Linked to Oral Cavity Manifestations Using an IoMT-Based Optimized Neural Networks. *IEEE Access*, **8**, 190722-33.

Heidari AE, Sunny Sumsum P, James Bonney L, et al (2019). Optical Coherence Tomography as an Oral Cancer Screening Adjunct in a Low Resource Settings. *IEEE J Sel Top Quantum Electron*, **25**.

Hu Z, Alsadoon A, Manoranjan P, et al (2018). Early-Stage Oral Cavity Cancer Detection: Anisotropic Pre-Processing and Fuzzy C-Means Segmentation. DOI: 10.1109/CCWC41889.2018, 8-10.

Jeng MJ, Sharma M, Chao TY, et al (2020).Multiclass classification of autofluorescence images of oral cavity lesions based on quantitative analysis. *PLoS One*, **2020**.

Jeyaraj PR , Panigrahi BK, Samuel Nadar ER (2020). Classifier Feature Fusion Using Deep Learning Model for Non-Invasive Detection of Oral Cancer from Hyperspectral Image. *IETE J Res*, **2020**, 13-1.

Morikawa T, Kozakai A, Kosugi A, et al (2020). Image processing analysis of oral cancer, oral potentially malignant disorders, and other oral diseases using optical instruments. *Int J Oral Maxillofac Surg*, **49**, 515-21.

Qiuyun Fu, Yehansen Ch, Zhihang Li, et al (2020). A deep learning algorithm for detection of oral cavity squamous cell carcinoma from photographic images A retrospective study. *E Clin Med*, **27**, 100558.

Rahman TY, Mahanta LB, Choudhury H, et al (2020). Study of morphological and textural features for classification of oral squamous cell carcinoma by traditional machine learning techniques. *Cancer Rep*, **3**, e1293.

Ren R, Luo H, Su C, et al (2021). Machine learning in dental, oral and craniofacial imaging: a review of recent progress. *Peer J*, **9**, e11451.

Sharma N, Nawn D, Pratiher S, et al (2021). Multifractal Texture Analysis of Salivary Fern Pattern for Oral Pre-Cancers and Cancer Assessment. *IEEE Sens J*, **21**, 7.

Shipu Xu, Yong L, Wenwen Hu, Chenxi Z (2019). An Early Diagnosis of Oral Cancer based on Three-Dimensional Convolutional Neural Networks. *IEEE Access*, **12**.

Tanriver G, Soluk Tekkesin M, Ergen O (2021). Automated Detection and Classification of Oral Lesions Using Deep Learning to Detect Oral Potentially Malignant Disorders. *Cancers*, **18**, 581-92.

Tanriver G, Soluk Tekkesin M, Ergen O (2021). Automated Detection and Classification of Oral Lesions Using Deep Learning to Detect Oral Potentially Malignant Disorders. *Cancers*, **13**, 2766.

Welikala RA, Remagnino P, Lim JH , et al (2020).Automated Detection and Classification of Oral Lesions Using Deep Learning for Early Detection of Oral Cancer. *IEEE Access*, **2020**.