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AN OVERVIEW OF THE LITERATURE CONCERNING THE IDENTIFICATION OF SUSPICIOUS REGIONS IN ORAL CANCER DETECTION AT AN EARLIER STAGE

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ABSTRACT

The major health issue of oral cancer affects people all around the globe. The majority of oral malignancies are discovered later, when therapy is less effective. Early early detection is crucial for several forms of cancer. The provision of required treatment measures that also benefit the patients is made possible by early diagnosis for surgeons. The X-rays known as dental radiographs are used to find issues with the teeth, mouth, and jaw. The many techniques that have been examined by researchers for the early detection of oral malignancies have been thoroughly reviewed in this publication. The different techniques for identifying and categorizing malignancies are contrasted. The algorithms used in each stage of the cancer detection algorithms are described.

INTRODUCTION

In the globe, oral cancer is the eighth most common cancer in women and the fourth most common cancer in males. It may affect the tongue, cheeks, peridontium, or any other region of the oral pharynx. The major health issue of oral cancer affects people all around the globe. The term "odontogenic tumor" refers to tumors that develop from tissues that generate teeth. Malignant or benign tumors both exist. Cancerous tumors are malignant tumors. Any part of the oral cavity, including the tongue, cheek lining, lips, gum tissues, and hard and soft palate, may develop oral cancer. The topic of this essay is early detection of oral cancer. Early oral cancer identification can save lives [1]. Numerous issues, in addition to oral cancer, may develop inside the mouth's bones. Systemic issues, or those that impact the whole body, often start in the mouth. Generally speaking, the mouth is an excellent predictor of what is happening in the body, which is why doctors have encouraged patients to open their mouths for decades. The use of X-rays is crucial in dental treatment. X-rays are useful diagnostic tools, but some dental offices, especially those that deal with a lot of dental implant patients, are adopting more sophisticated imaging methods to guarantee an even better level of accuracy. Because oral tumors are often found on the tongue, moving artifacts brought on by the tongue and jaw movement may cause MR images to seem fuzzy. Therefore, a powerful image processing method is required to accurately detect the suspicious region in the cancer area. Dental radiographs are often used to check for oral diseases, however it might be challenging to find cancerous tissues in their early stages. While oral cancers may often be visible with the unaided eye, unlike other cancers, some are internal to the mouth, making early identification challenging. Additionally, certain tissues that are not malignant are safe.

The chapter is structured as follows: A literature review on cancer has been done in section 2. Sub Section 2.1 presents a few of the most modern cancer detection techniques. The techniques for feature extraction and cancer classification are covered in Sub Section 2.2. Section 3 includes discussions of the methods. The part is concluded and summarized in part 4.

LITERATURE SURVEY

Oral cancer is treatable if discovered at an early stage. Although the precise etiology of cancer is unknown, there are several risk factors that might make someone more susceptible to the condition. Chemicals, which may be found in cigarettes or in food, air, water, etc., are among the frequent causes [2]. These substances are referred to as carcinogens. One of the most important areas of study in the medical imaging and image processing communities is cancer detection and diagnosis.

Symptoms:

Early signs of oral cancer include [3] the following: 1) White, red, or mixed white and red patches on the lips or within the mouth 2) Any mouth sore or region that is stained for more than 14 days without healing Three) Mouth bleeding 4) Difficulty swallowing or discomfort A neck lump (number five). These signs point to malignancy as the likely culprit. With the use of image processing techniques, the system detects the presence of cancer.

Few alternatives are available to a surgeon who suspects cancer in a patient: Excision of a section of the unhealthy tissue for a biopsy, removal of the cancer, and exploration of the surrounding tissues to ascertain if the cancer has spread are all methods used to detect the precise site of the cancer.

Refinements in imaging technology over the last several decades have significantly increased the variety of medical options:

The images of organs and tissues provided by the tests are now more crisper and more comprehensive.

We can now do more than just look at anatomical features like bones, organs, and cancers thanks to advances in imaging technology.

Real-time monitoring of physiological processes like blood flow, oxygen consumption, or glucose metabolism is made possible by functional imaging, which is the viewing of physiological, cellular, or molecular activities in live tissues.

Imaging technology has already made it possible to diagnose cancer more precisely and identify cancer early, which may save lives. In order to get improved outcomes, image processing [4] methods have been regularly employed. According to the literature review that was done, there has been some study done on cancer imaging.

Cyst identification and cyst severity evaluation utilizing image processing techniques and neural network approaches have been suggested by Cancer identification Techniques [Banumathi.A et al 2009] [5]. Radial Basis Function Network is used to identify the cyst areas that are perhaps worrisome. Circularity values are used to determine the cysts' severity, and the results reveal the cysts' removed portion.

Woonggyu Jung and others [6] has suggested a method for employing optical coherence tomography to diagnose oral cancer. Oral mucosa may be imaged with OCT at depths of 2 to 3 mm. In 3-D volume scans of benign and precancerous lesions, they also found oral cancer.

Peter Kent [7] has suggested utilizing genetic programming to diagnose oral cancer. Many challenging issues were resolved by the suggested Technique. A comparison between a neural network model and a genetic programming system was given. The tumor's diagnosis benefited greatly by the use of the Genetic Programming technology.

Rajan Rashmi Paul and others Oral cancer diagnosis using wavelet-based neural networks has been suggested by [8]. The feature vector that was utilized to train the artificial neural network was selected using the wavelet coefficients of TEM images of collagen fibers from healthy oral sub-mucosa and OSF tissues. The trained network may accommodate both precancer and normal phases.

[Dr. S. Thamarai Selvi and Ireaneus Anna Rejani.Y. 2009] [9] have suggested a method for applying SVM Classifier to identify breast cancer at an early stage. The suggested system concentrated on two issues. One method is to identify tumors as suspicious areas that contrast extremely weakly from their surroundings, and another is to extract attributes that classify tumors. For picture enhancement, they employed the Gabor filtering approach, and for image extraction, they used the Top Hat transform operation.

[Dr. K. Satya Prasad and Saheb Basha.S. 2009] [10] have suggested employing morphological procedures and fuzzy C-means clustering to automatically identify breast cancer mass in mammography. Through the use of morphological operators and the fuzzy C- means clustering (FCM) method, they created an algorithm to separate masses and microcalcifications from background tissue. The suggested method produced superior outcomes.

2007 [Man Kin Derek Ho] An approach to segment pictures for medical confocal imaging has been proposed by [11]. The findings show a precise (95% with a 6.2% standard deviation) count of the cells or droplets. Tomas Gustavsson, Artur Chodorowski, and Ghassan Hamarneh, 2000 In order to segment oral lesions in medical color pictures obtained from the visual portion of the light spectrum, [12] have suggested the use of active contour models. In the proposed study, lesions are divided into malignant and non-cancerous categories. The automated segmentation technique makes it easier to analyze oral lesions and may be utilized in clinical settings to find lesions that could be malignant.

[V. Rajamani, S. Murugavalli, 2007] [13] suggested segmentation based on neuro fuzzy method as a better way to identify brain tumors. There were many tissues found, including tumor, cuff, white matter, and gray matter. The picture is categorized layer by layer using the fuzzy C means technique. The neuron fuzzy approach demonstrates that HSOM-FCM-based MRI brain tumor segmentation also performs more accurately.

Muhammad.M.M. et al., 2003 [14] has suggested using the segmentation of the ultrasound image's Gabor filter texture to diagnose prostate cancer. An great technique for examining prostatic texture is multichannel filtering. Medical professionals analyze texture using three aspects, namely repetition, directionality, and complexity, using the human visual system (HVS). An good technique for prostate texture segmentation is a series of Gabor filters that closely resemble the HVS and are evenly dispersed throughout the whole frequency plane.

[Kandasamy, A., and Seshadri, H.] [15] has suggested using digital mammogram image analysis to identify breast cancer at an early stage. The segmentation method is then used to the preprocessed picture after calculating the gradient of the image.

On digital mammograms acquired from the mini-MIAS database, they used the suggested approach for testing, and they discovered that the lesion segmentation algorithm closely matched the radiologists' outlines of these lesions.

An automated technique was suggested by Varsha.H. Patil et al. [16] for identifying breast tumors sooner. The system displays the required data to support the doctor's diagnosis using a super resolution approach. The system was created using CAD software.

According to Poulima Das et al. [17] have recommended further pathology testing and a way to detect aberrant growth cells in breast tissue. Through a set of image processing stages, they contrasted healthy breast tissue with malignant invasive breast tissue. The characteristics of breast malignant tissue are taken out and compared to healthy breast tissue.

[2011, Shekar Singh et al.][18] have suggested classifying histological pictures and detecting breast cancer. They classified benign and malignant breast tumors using a feed-forward back-propagation neural network. Type 1, Type 2, and Type 3 were the different subtypes of breast cancer. Following the discovery of cancer, eight characteristics were retrieved. Breast cell nuclei are quickly and precisely classified by a feed-forward neural network.

Utilizing a variety of methods, computer assisted diagnostic systems for identifying cancerous texture in biological studies have been studied. Using texture characteristics and neuro classification logic, Vijay Kumar.G et al [19] suggested a method in computer assisted diagnostics for the early prediction of brain cancer. For the prediction of a tumor in a certain MRI picture, nine unique invariant characteristics with the computation of the minimum distance were used. The extraction area is recognized using a neurofuzzy technique.

An active contour model-based Hopfield neural network was proposed by Yan Zhu and Hong [20] for the identification of brain tumor borders. Real-time applications might benefit more from this.

The need of great precision when dealing with human life motivates the automated diagnosis of cancers in various medical imaging. In order to detect brain-related disorders, L. Jeba Sheela et al. [21] devised a method employing imaging techniques to classify the pictures as normal or abnormal and then classify the tissues of the aberrant brain MRI.

Feature extraction and cancer classification techniques

[DSVGK Kaladhar, P. Bharath Kumar, and B. Chandana, 2011] [22] have used classification systems to forecast oral cancer survival. CART, Random Forest, LMT, and Naive Bayesian are the classification methods employed. The algorithms use a 10-fold cross-validation and training data set to categorize cancer survival. The Random Forest classification methodology distinguished the cancer survival data set properly from the other methods. When compared to other techniques, the absolute relative error is lower.

The authors [Xiaowei Chen et al. Automated segmentation, classification, and tracking of cancer cell nuclei in time-lapse microscopy have been suggested by [23]. Such time-lapse datasets are difficult to analyze and monitor with current computational imaging techniques, and manual analysis might take an excessive amount of time and be vulnerable to observer bias. To close this gap, an automated system that incorporates a number of cutting-edge analytical techniques is needed. The techniques for cellular image analysis may be used to segment, categorize, and monitor individual cells over the course of a few days in a population of live cells. The suggested technique is successful and efficient for cell tracking and phase identification, according to experimental findings.

[Yung-neon Sun et al. 2010,] A color-based feature extraction technique for parameter estimation of oral cancer from optical microscopic images has been suggested by [24]. Only the mean parameters between early and late cancer stages are statistically different when four cancer stages are compared in terms of parameters. An efficient and practical tool for the automated segmentation and assessment of stained biopsy samples of oral cancer is provided by the suggested system.

Sun, Yung-nien, et al., 2007. A brand-new color-based method for the automatic segmentation and categorization of tumor tissues from microscopic pictures has been put forward by [25]. By comparing the effectiveness of the suggested fully automated approach with semi-automated processes, the algorithm is assessed. The experimental findings reveal strong agreement between the two approaches. The suggested method offers a useful instrument for assessing oral cancer pictures. It may be used on further microscopic pictures created using the same tissue staining method.

In 2011, Neha Sharma, Nigdi Pradhikaran, and Akurdi The effectiveness of data mining strategies for predicting oral cancer has been compared by [26]. The two data mining methods used are the tree Boost model and the multilayer perceptron neural network model. Multilayer Perceptron Neural Network and Tree Boost show the same specificity and sensitivity for both training and validation data. In training and validation data for Multilayer Perceptron Neural Network and tree boost model, there is no misclassification of data. The "Presence of Lymph Node" as shown on USG is also the most significant determinant for the prognosis of malignancy. According to the research, both the Tree Boost Classification Model and the Multilayer Perceptron Neural Network Model are best at predicting a patient's propensity for malignancy.

Chandran Chakraborthy, M. Muthu Rama Krishnan, and Ajoy Kumar Ray, 2010. A wavelet-based texture categorization for oral histopathology sections has been suggested by [27]. A novel approach is suggested since the existing method introduces stain intensity, inter- and intra-observer differences that increase misclassification error. The suggested approach includes feature extraction using wavelet transform, feature selection using Kullback-Leibler (KL) divergence, and diagnostic classification using the Bayesian Approach and Support Vector Machines. [A. Chodorowski and others, 1999] [28] have suggested a technique for classifying oral lesions based on real color photographs. The use of five distinct color representations for color image analysis of mucosal pictures was investigated and assessed. For the assessment of classification performance, four popular classifiers (Fisher's Linear Discriminant, Gaussian quadratic, KNN closest neighbor, and Multilayer Perceptron) were used. Resubstitution and five-fold cross validation techniques were used to

measure classification accuracy. HIS system and linear discriminant function produced the best classification results.
(2008) A. Ji Wan Han [29] have looked at how radicular cysts and odontogenic keratocysts are classified. Cascaded haar classifier was used to classify the data. For each form of cyst, three distinct classifiers were trained to evaluate unseen histology pictures one at a time and output a statistical count of the presence of each matching cyst nuclei type. The outcomes of the experiments demonstrate how well these classifiers locate and categorize the nuclei of individual cells.

The idea of mammographic feature augmentation by multiscale analysis was first out by [Laine. A.F et al] [30]. Three overcomplete multiscale representations are used to explain three different contrast enhancement techniques: Three wavelet transforms—the dyadic wavelet (separable), the wavelet (non-separable, nonorthogonal), and the hexagonal wavelet (nonseparable)—are available. Local assistance for picture improvement is provided by multiscale edges located inside various layers of transform space.

In order to predict the recurrence of oral cancer, [Sebastian Steger, Marius Erdt, Gianfranco Chiari, and Geirgious Sakas] [31] have presented a unique picture feature extraction strategy. Also suggested are a number of numerical imaging characteristics for tumors and lymph nodes. Automatic extraction of certain traits is necessary. The foundation for automated extraction of geometric and texture properties of tumor and lymph nodes is registration and supervised segmentation of CT/MR images. Compared to current clinical practice, more accuracy and robustness are attained.

A review of the literature suggests that one of the current research hot spots is cancer imaging. Researchers believe that early cancer detection, segmentation, and classification are crucial. The researchers in this field have helped to build algorithms for cancer detection, segmentation, classification, and other related tasks.

COMPARISON OF METHODS

Comparison of Cancer Detection Techniques

A neural fuzzy model was used in [13] to increase the value of tumor pixels. Layer by layer, the picture is classified by the algorithm. A Neuro Fuzzy model was used to find a brain tumor. Tumor pixels were recognized and the performance of the MRI picture was assessed in terms of weight vector, execution time, and tumor pixels. The detected tumor pixel reached the highest value ever.

Snakes were used by Ghassan Hamasneh et al. [12] to semi-automatically segment oral lesions in color photographs of the human oral cavity. When compared to conventional edge-based segmentation, snakes resulted in fewer tiny segmentation mistakes and required less edge connecting. However, because to the high level of unpredictability in the objects and pictures in this application, operator intervention was required. The initial step in [8] is figuring out the seed areas. In order to serve as a better classifier, the fuzzy C-means clustering method is utilized as part of a segmentation approach with the goal of classifying data into distinct groups based on their features. More and more details about the tissue that pathologists are unable to identify are learned as the number of clusters rises.

An automated technique was suggested by Varsha.H. Patil et al. [16] for identifying breast tumors sooner. The technology was interactive and online, making it quicker and more accurate than a manual method. The system displays the required data to support the doctor's diagnosis using a super resolution approach.

The suggested method produced encouraging segmentation results in [15]. However, a few control parameters are not automatically determined, and more work has to be done on lesion detection. A new approach is suggested for the future to extract several factors that define each basin. These variables will be used with the goal of automatically identifying lesions that may be questionable.

For the early identification and diagnosis of oral premalignancy and cancer, Woong et al. [6] employed 2D and 3D OCT. Anywhere and whenever the doctor chooses, 3D pictures provide precise structural information. OCT has the potential to be a formidable tool for the early diagnosis of oral cancer.

Methods for Cancer Classification Comparison

Oral tumor was categorized by Muthu Rama Krishnan et al. [27] using Bayesian Classification and Support Vector Quantization. To establish the meaning of a measurement, the whole wavelet family has been employed as an input to a classifier. 9 wavelet characteristics of the epithelium and 48 gabor wavelet features are retrieved. KL divergence is used to assess each feature's significance. Wavelet- and Gabor-wavelet-based texture characteristics are also used to improve classification accuracy. Wavelet family with gabor texture characteristics yields a Support Vector Quantization classification accuracy of 92% on average and a Bayesian classification accuracy of 76.83%.

Ji Wan Han et al [29] classified data using the Haar cascade classifier. Although the classifiers were able to locate individual cell nuclei, they often detected false positives. These erroneous detections have a detrimental effect on the technique's overall categorization outcomes. The performance of this approach in comparison to that of [30] is based on fewer data, however. In accordance with the conventional cell isolation based technique, Landini [32] used image processing algorithms to analyze the epithelial lining architecture in radicular cysts and odontogenic keratocysts.

Thresholding was employed by Ireaneus Anna Rejani.Y et al [9] to segment their data. SVM classifier is used to categorize breast cancer. 75 mammographic pictures from the mini-MIAS database were used to test the approach. A sensitivity of 75% was reached using the methods.

A. Chodorowski et al. [28] suggested a technique for classifying oral lesions based on real color photographs. RES resubstitution and 5-fold cross validation techniques were used to measure classification accuracy. The HSI color scheme with a linear discriminant function produced the best classification results, with a 94% accuracy rate. Table 1 contains comparisons of several approaches.

DISCUSSION

There are several methods for finding malignancies. For classifying tumors, several researchers have recommended using neuro-fuzzy models. Numerous techniques strive for great accuracy, more features, and improvements. According to [19], the accuracy level is roughly 50–60% higher in recognition when compared to the previous neural classifier, despite the lengthy iteration time. In [20], the active contour model is a key factor in achieving the intended detection. Consequently, an adaptive active contour model was adopted in this study. By changing the model and neural network training method, the accuracy and speed of detection may be further altered. These articles emphasize accuracy more so. However, due of the moving artifacts produced by the moving tongue and mouth, the procedures used for breast tumors or brain malignancies cannot be used directly to oral cancers.

CONCLUSIONS

This essay analyzes several cancer detection techniques. The planned research would detect oral cancer sooner, enabling surgeons to provide the right drugs and other therapies for the specific form of disease. The proposed work will investigate various enhancement methods to enhance the quality of images captured by imaging devices like X-ray, MRI, Ultrasound, Positron Emission Tomography (PET), Optical Imaging (OI), Computed Tomography (CT), and Positron Emission Tomography. The people with oral cancer will profit from this.

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