Performance Analysis of GFE, HOG and LBP Feature Extraction Techniques using kNN Classifier for Oral Cancer Detection

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Abstract – Oral cancer is the abnormal growth of suspicious tissues in the mouth and vocal region that consumes the life of both males and females at a high rate. Early diagnosis of oral cancer makes the treatments successful. The advancements in medical image processing greatly helps in the detection of oral cancer. The diagnosis is commonly done in accordance with the morphology and features of the images. The commonly used feature extraction techniques failed to produce high accuracy and resulted in high false positive rates. As the extracted features are the base for classifying the severity, the classification techniques also resulted in low classification accuracy. In order to resolve these issues, this paper proposes an oral cancer detection system. The median filtering technique is used in the proposed system for preprocessing. In order to get the essential characteristics of features, watershed segmentation is applied before feature extraction. The feature extraction is carried out by the following techniques: Gamma based Feature Extraction (GFE), Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP). Finally, the extracted features are fed into the kNN classifier for the efficient detection of oral cancer. This paper discusses the comparative analysis of HOG, LBP and GFE techniques. The experimental results are evaluated in terms of accuracy, sensitivity, specificity and Positive Predictive Value (PPV).

Index Terms – Oral Cancer, kNN classifier, watershed segmentation, median filtering, Gamma based Feature Extraction (GFE), Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP).

1. INTRODUCTION

Oral cancer is chronic disease that leads to high mortal rate and is common among both the males and females. The oral cancer is an abnormal growth of the unwanted tissues in the areas of mouth, jaw, tongue, jaw bone, lips, cheeks and gum tissues. Like all cancer disease, the oral cancer is also classified into two categories including benign and malignant oral cancer. If the oral cancer is identified at its earlier stage, it is termed as benign cancer. The benign cancer do not spread and invade the other tissues, and it can be treated using several advanced medical techniques including chemotherapy, surgery and radiation. The malignant cancer is the cancer identified at the matured stage that leads to high mortality rate. At this stage, no advanced medicine is able to save the life of the patient. In general, the oral cancer is caused due to the usage of tobacco, cigarette smoking, and pan usage and alcohol consumption. The other factors that lead to oral cancer are age factor, genetic factor, insufficient diet and the exposure to the Ultra Violet (UV) radiations from the sun. The oral cancer can be identified by the presence of red and white patches, soreness and irritations, swollen jaws and ear pain. Biopsy is the most common treatment for oral cancer, in which a sample tissue is examined for the presence of suspicious cells. It is a painless treatment performed by the dentists at the early stages for diagnosis. In addition, the chemotherapy eradicates the cancer cell through drugs and the radiation is also passed to the cells in radiotherapy. The process of self-examination and regular dental care and visit to the dentists helps in the prevention of oral cancer.

Due to the advancements in the medical and computer technology, the oral cancer can be identified by several techniques including neuro-fuzzy techniques, image processing techniques and data mining techniques. Even though, there are several techniques, the image processing is considered as the best way for diagnosis because of the evolving progression of medical image processing. Among, the medical imaging techniques, the auto fluorescence imaging is applied for the identification of oral benign lesions. In order to reduce the subjective interpretation of auto fluorescence imaging, the digital fluorescence imaging is introduced. But, it resulted in high false positive rates. As the raw images generated the inaccurate results, the images are processed using the medical image processing techniques. The images are preprocessed to screen the cancer cells based on the characteristics and features of the oral images. The preprocessing step eliminates the inconsistent and irrelevant pixels of the images. The unwanted background regions are removed by segmentation process to focus on the cancer affected regions. From the cancer affected regions, the most significant features required for detecting the cancer severity is collected via feature extraction step. The extracted features are trained using the training dataset, which helps to improve the classification accuracy. At the testing stage, the images are categorized either as malignant or benign cancer.

The issues in the traditional oral cancer detection techniques are as follows:

- It is difficult to separate the foreground and background objects having same intensities.
- It resulted in high false positive rates, thereby producing less accurate results.

The above mentioned shortcomings are addressed in the proposed oral cancer detection system. The proposed method used median filter for preprocessing and watershed segmentation for segmenting the required regions. As the segmentation is done based on the morphological characteristics, the difficulty in segmenting the same intensity pixels are resolved. Three feature extraction techniques, namely, Gamma based Feature Extraction (GFE), Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP) are utilized for feature extraction. The false positive rates are reduced by the kNN classification algorithm. Finally, the performance of the three feature extraction techniques are compared in terms of sensitivity, accuracy, PVV and specificity.

The remaining sections of this paper are organized as follows: Section II surveyed the traditional techniques for feature extraction and classification in image processing. Section III provides an overview of the proposed system for the efficient detection of oral cancer. Section IV shows the performance analysis of the proposed system. Section V gives the conclusion of the work.

2. RELATED WORK

This section reviews several image processing existing technique to detect oral cancer. *Krishnan, et al.* [1] proposed a hybrid feature extraction technique for detecting oral cancer in histopathological images in an automated way. The efficiency of the proposed technique was enhanced by the integration Local Binary Pattern (LBP), Higher Order Spectra (HOS) and Laws Texture Energy (LWE) techniques. The benign and malignant tissues were categorized by a novel index, namely, Oral Malignancy Index (OMI). The results attained by the Fuzzy classifier along with the HOS feature extraction technique achieved higher accuracy, specificity and sensitivity. *Anuradha and Sankaranarayanan*[2] reviewed different feature extraction techniques in image processing for classifying the oral cancer. The Region of Interest (ROI) approach is used for preprocessing and the images were segmented by the marker controlled watershed segmentation technique. The histogram intensities of Gray Level Run Length Matrix (GLRLM) and Gray Level Co-occurrence Matrix (GLCM) techniques were integrated for mining the actual features. The severity of the tumors were classified using Support Vector Machine (SVM). The results of this approach resulted in higher classification rate. *Zheng, et al.* [3]proposed a hybrid feature extraction technique by combining K-means and SVM algorithm to diagnose the breast cancer. The hidden patterns of the images were recognized using the K-means algorithm. The accuracy of the proposed technique was enhanced by the 10-fold cross validation method. Various properties of the images were easily understood using the suggested technique.

Lambin, et al. [4] proposed a feature extraction technique, namely, radiomics to extract the information through feature analysis. The application of radiomics for cancer detection eliminates the use of biopsy. The results showed that the throughput of feature extraction was improved in radiomics. Chadha, et al. [5]reviewed different feature extraction techniques such as local and global color histogram, color moments, co-occurrence matrix, average RGB, and geometric moment. For each image, four matrices were generated, and four main features such as energy, entropy, contrast, and homogeneity were used in feature extraction. The combined approach provided excellent accuracy but with poor redundant factor and long retrieval times. Cropping the image reduced the unwanted information of an image, and there was an improvement in accuracy by 28%. Anuradha and Sankaranarayanan [6]proposed a segmentation and feature extraction based image processing technique for oral cancer identification. The proposed approach applied Marker Controlled Watershed Segmentation (MCWS) to segment the images. The essential features were extracted through Gray Level Co-occurrence Matrix (GLCM). The gray level run length matrix was used to extract the higher order statistical texture measures. The severity of the tumor was categorized using SVM. The GLCM and GLRLM were compared with the intensity histogram, and the classification rates of each method were 96%, 92%, and 88% respectively. Bhuiyan, et al. [7]eliminated the biopsy treatment to prevent the invasive issues for oral cancer patients. The issues of biopsy were resolved by the analysis of unsupervised segmentation techniques based feature extraction. The, Asymmetry Index (AI) value and Lengthening Index (LI) value were computed to measure the pixel similarity. The results showed that this method was quite effective under the proper segmentation. Dhawan and Dogra [8]survey edvarious facial feature extraction techniques including color segmentation-based, template-based, geometry-based, and appearance-based feature extraction. The analysis resulted in higher recognition rate for template based approaches, when compared to geometry based and appearance based approaches.

Adegoke, et al [9]studied the fundamentals of image processing and surveyed the techniques applied for feature extraction. A subset of relevant features from a group of features of the image was selected, which helped in acquiring better understanding about the image by increasing the number of features. Baboulaz and Dragotti [10] proposed a novel technique to process the image is low resolution and quality. The low level features of the images including corners and step edges were identified by sub-pixel extraction. The Heaviside function was used to express a straight continuous step edge mathematically. When compared with the previously used local extraction algorithms, this technique obtained super-resolved images with better quality. Kamavisdar et al. [11] surveyed various classification techniques such, as Decision Tree (DT), SVM, ANN, and fuzzy classification. In supervised classification, known informational classes were used to classify pixel of unknown identity, whereas in unsupervised classification, a large number of unknown pixels were examined based on the natural groupings present in the image values. The results were not highly accurate because of the mixed pixel problem. SVM used a non-parametric approach with binary classifier to handle a large amount of input data in a more efficient manner.

Herrera, et al [12] proposed a crowdsourcing platform Crowd flower to improve the accuracy of the automatic training set expansion, and many machine learning tasks. The case-band task retrieved the cases that were similar to the query case to perform differential diagnosis. Thus, manual correction noisy training set improved the performance, and crowdsourcing provided strict quality control at a very limited cost. Camlica, et al. [13] proposed a classification technique using the Local Binary Pattern (LBP) features in a SVM classifier to detect salient regions of images during training, and to fold the data to reduce the effect of irrelevant regions. This approach comprises of preprocessing phase, offline training, and online usage phase. The saliency maps were extracted, and the images were folded during preprocessing. Folding was done to reduce the image area without any information loss. The SVM gained higher classification score with less computational complexity and low storage requirements. Varalakshmi [14] proposed a hybrid approach to identify all nodules form the chest CT lung images, and to classify these nodule into cancerous and non-cancerous nodules. The suggested approach integrated the ANN approaches and image processing techniques. In the hybrid approach, the lung images were segmented using threshold technique, and extracted using morphological operations. It resulted in low false positive rate. El-Ashmawy, et al. [15] proposed a pixel-based classification technique using a maximum likelihood classifier. In pixel-based classification, intensity data was imported, and training signatures were identified for the four different classes. The images were categorized according the intensity of pixels. The pixel based classification outperformed the existing techniques.

3. PROPOSED METHOD

This section describes the overview of the techniques applied for the proposed system for oral cancer detection. The overall flow of the oral cancer detection system is illustrated in Fig 1.

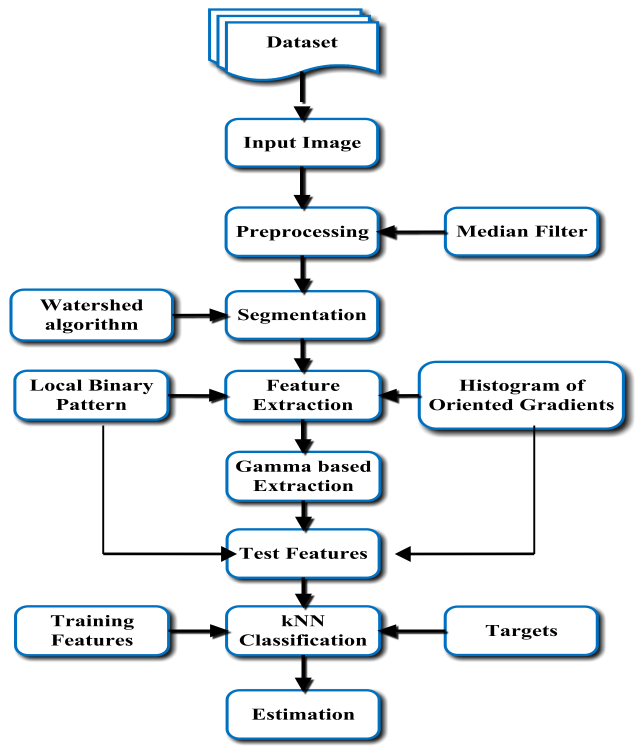

Fig 1 Overall flow of the proposed oral cancer detection system

The proposed system for oral cancer detection includes the following stages:

- Preprocessing
- Segmentation
- Feature Extraction
- Classification

A. *Preprocessing*

Image preprocessing is the initial and fundamental step in digital image processing. The main intent of preprocessing is to improve the visual quality of the image and to enhance the dataset. Fig 2 (a) shows the raw image from the oral cancer dataset. The preprocessed images is depicted in Fig 2 (b). Generally, the images have unknown noise, in homogeneity, poor image contrast, unrelated body parts, and weak boundaries. The random disturbances degrades the image quality and thus, preprocessing can be applied to remove the degradation phenomenon. Commonly, the filtering techniques are used for the elimination of noise.It also removes the noise and regenerates the distorted images by bridging the small gaps at the corners and edges.

In the proposed oral cancer detection system, the median filter is applied for preprocessing. The median filtering is a simple and effective filtering technique that is used to eliminate the impulse noise from an image. A square window of variable size is used to cover the pixels, whose median is to be found. The pixels values covered by the window is sorted in the ascending order to find the middle value. The central pixel of the image is replaced by the found median value. Each and every pixel value is compared with the neighboring pixels to classify the noise present in an image. Then, median pixel value replaced the pixel values of the remaining pixels.

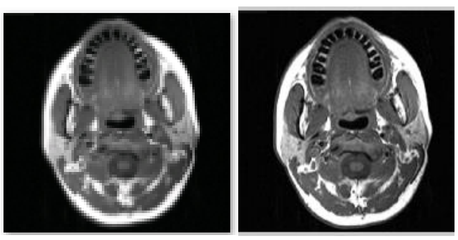

Fig 2 (a) Before Preprocessing (b) After Preprocessing

B. Segmentation

In oral cancer detection, it is significant to extract the required information from the preprocessed images. Hence, segmentation plays a vital role in the process of information extraction. The regions of the preprocessed oral images are segregated into exclusive and exhausted regions. Fig 3 (a) and (b) denotes the images before and after segmentation respectively. The proposed oral cancer detection system applies watershed segmentation to resolve the issues in the over segmentation of images. The process of merging and removing the fake regions enhances the segmentation efficiency. It also eliminates the insignificant regions and the background noise. The neighboring regions with high similarity are found using the similarity function.

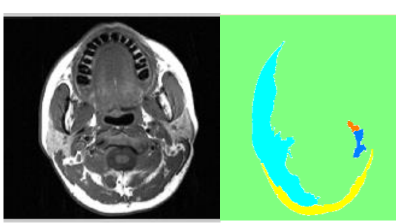

Fig 3 (a) Before segmentation (b) After segmentation

C. Feature Extraction

Feature Extraction is the process of describing the characteristics of the image or the set of features in the image, which is efficient and meaningful in the representation of information in the image. The extracted features are useful in the analysis and classification of images. The relevant features are derived from the original feature set that contains an initial set of measured features. The derived features are informative, non-redundant, and facilitate the learning of the features. The feature extraction is related to the dimensionality reduction of the image. The reduced set of features is also termed as the feature vector. In the proposed oral cancer detection system, three feature extraction techniques, namely, LBP, HOG and GFE is applied to get the highly accurate features. The extracted features are depicted in Fig 4.

Fig 4 Feature extracted image

1) Local Binary Pattern (LBP)

In LBP, the pixels in the segmented images are denoted as binary format. The LBP operator considers eight neighborhood pixels and the value of the central pixel is assigned as the threshold value. Then, the pixel values are compared with the value of the central pixel. If the value is greater than the threshold value, the pixel is accepted, otherwise, it is rejected. It detects the lines, edges, spots and angles in the images and reduces the memory consumption. The LBP code for the images are computed by building the histograms. The presence of micro-patterns over the images are identified by the constructed histogram. The features are extracted by partitioning the segmented regions into several equal sub-regions. The global shape and the local texture of the images are obtained as a result of LBP operation.

2) Histogram of Oriented Gradients (HOG)

The HOG technique is applied for feature recognition, where the precise information are extracted using the dissemination of intensity gradients and local shape characteristics. The images are normalized to attain the illumination invariance. Before the application of HOG, the image is divided into small sub cells.

3) Gamma based Feature Extraction (GFE)

Gamma correction is generally one of the image preprocessing techniques that compensates the distortions in a non-linear manner. The luminance of an image is enhanced using the Gamma correction technique. In the proposed technique, the Gamma correction is applied for extracting the features from the oral images. According to the voltage and luminance ratio, the correct features are obtained from an image. The saturation of the image is altered by adjusting the value of pixels in a non-linear fashion. A constant value is added to each pixel and the mean intensity values are shifted throughout the whole image. The GFE improves the feature extraction accuracy on combination with HOC and LBP.

D. Classification

In image classification, the reduced feature space is divided into non-overlapping regions and they are grouped under separate classes with unique labels. After the images are classified, the accuracy of the classified image is compared to that of the unclassified image. The main objective of classification is to partition all the pixel values in a digital image into several groups or classes. It is the process of separating the images based on the known and the unknown identity of the pixel values. Image classification involves two phases in the processing of images such as the training or the learning phase and the testing phase.

1) K-Nearest Neighbor (kNN) Classification

The kNN classifier is one of the non-parametric classification technique. A feature set $S = \{s_1, s_2, \dots s_i\}$ consists of a set of distinct features, where s_i is the i[th] feature. The distance measure among the neighboring pixels are computed by finding the distance between an individual instances in the feature set and its neighbors. The Euclidean distance is used to determine the membership proximity.

$$d(Q, s_i) = \sqrt{\sum_{i=1}^{m} (Q - s_i)^2} \quad (1)$$

Where, Q is the query image.

When compared to the SVM classifier, the computation complexity of kNN is low. The purpose of this kNN classification technique is to assign an unlabeled data sample to the class of its k nearest neighbors. The main intent of kNN classification is to determine a set of images from the training dataset that resembles the input image. The kNN classifier can be conveniently used as a benchmark for all the other classifiers, since it is likely to provide a high classification accuracy in most of the applications. The kNN classification technique can achieve high accuracy and false positive rates, with the improved computational efficiency.

K – Nearest Neighbor Algorithm

Input: Feature Set $S = \{s_1, s_2, \dots s_i\}$ that contains the extracted features

Q: Query Image

Output: Classified images based on the mean value

Begin

$S = \{s_1, s_2, \dots s_i\}$

Init Vector c, t

For

i = 1 **to**s_i

Do

Compute distance d (Q,s_i) according to (1)

End for

For each

If $Q < d(Q, s_i)$

$Q \leftarrow d(Q, s_i)$

Else

$t \leftarrow s_i$

End for

Store Q into vector c and t into S

Calculate the mean of the S

$$mean = \frac{1}{M} \sum_{i=1}^{M} s_i$$

Return mean as the output for the Query image Q

End

4. PERFORMANCE ANALYSIS

This section compares the performance results of the three feature extraction techniques such as GFE, HOG and LBP. For evaluation, fifty images are taken from the histological OSF image dataset. The performance of the proposed is analyzed using the following metrics.

- Accuracy
- Sensitivity
- Specificity
- Positive Predictive Value (PPV)

E. Accuracy

Accuracy is defined as the ratio of number of correct assessment to the total number of assessments. It is the number of relevant images retrieved from the total number of relevant and irrelevant images in the dataset. It deals with data quality and errors in the dataset. It is measured in terms of percentage (%).

$$Accuracy = \frac{(TN+TP)}{(TN+TP+FN+FP)} \quad (2)$$

Where, TN-True Negative, TP-True Positive, FP-False positive and FN-False Negative.

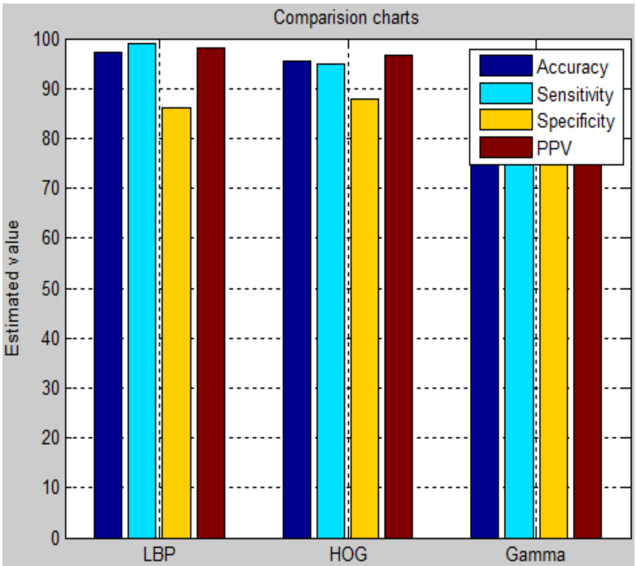

Fig 5 Performance analysis of LBP, HOG and GFE techniques in oral cancer detection system

Table 1 Comparison table of feature extraction techniques

Feature Extraction Techniques	Accuracy (%)	Sensitivity (%)	Specificity (%)	PPV (%)
LBP	97.08	98.98	86	98
HOG	95.5	95	88	96.53
GFE	93.7	93.4	90.6	94.72

F. Sensitivity

Sensitivity is defined as the ratio of the number of true positive assessments to the total number of true positive and false negative assessments. It is a degree of positive values that are correctly identified. It is measured in terms of percentage (%). It is a measure of true negative values that classifies the normal images from the dataset.

$$Sensitivity = \frac{TP}{(TP+FN)} \tag{3}$$

G. Specificity

Specificity is defined as the ratio of the number of true negative assessments to the total number of true negative and false positive assessments. It is used to predict the impact of changes in the output due the change in the input dataset. It is a degree of negative values that are correctly identified. It is measured in terms of percentage (%). It is a true positive measure that represents the correct classification of tumors from the oral image.

$$Specificity = \frac{TN}{(TN+FP)} \tag{4}$$

Fig 5 shows the performance analysis graph for the feature extraction techniques and Table 1 illustrates the comparison table. The GFE attained 93.7% accuracy, whereas HOG and LBP techniques 95.5% and 97.08% of accuracy respectively. Among these techniques, LBP technique achieved higher accuracy than the other two techniques. From this graph, it is depicted that the sensitivity of LBP technique is higher than the remaining techniques. The sensitivity attained by HOG and GFE are 95% and 93.4% respectively, whereas the LBP attained a higher sensitivity of 98.98%. When compared to the HOG and GFE techniques, the specificity value of LBP is higher. The specificity of HOG is 88%, GFE is 90.6% and LBP achieved specificity of 86%.

H. Positive Predictive Value (PPV)

The PPV is defined as the ratio of true positives to the sum of true and false positives. It is measured in terms of percentage (%). The rate of PPV rely of the disease prevalence images present in the dataset. The PPV comparison for the GFE, HOG and LBP techniques are shown in Fig 5. The GFE attained 94.72% PPV, HOG achieved a PPV of 96.53% and the LBP attained 98% of PPV.

$$PPV = \frac{TP}{(TP+FP)} \tag{5}$$

From the performance analysis it is clearly understood that the LBP feature extraction technique outperformed the GFE and HOG feature extraction techniques in terms of accuracy, sensitivity, specificity and PPV.

5. CONCLUSION

This paper proposed an oral cancer detection system to identify the cancer by the classification of oral images. As the raw images cannot be used for efficient detection, the images are preprocessed by the median filtering technique. The watershed segmentation technique is applied for image segmentation. By using the watershed segmentation, the images are segmented based on the image characteristics. The features extracted by the three techniques such as GFE, HOG and LBP are used to enhance the accuracy in cancer detection. The resulting features of these techniques are fed to the kNN classifier. The computational complexity in classification is reduced by the kNN classifier. The results obtained from the HOG, LBP and GFE techniques are compared. For performance validation, the histological OSF images are trained and tested in the classification phase. The results proved that the LBP feature extraction technique achieved high accuracy, sensitivity, specificity and positive predictive value with reduced false positive rates.

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