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# Periapical Dental X-Ray Image Segmentation by Using K- Means Clustering

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**Abstract -** Dental Imaging X rays, also called as Intra Oral Periapical Xrays (IOPA) are used for the diagnosis in clinical application in real time and can be segmented using various image processing techniques. These segmentation techniques are used to define the segmentation of Dental x rays , which are used to identify caries lesions, fracture of the dental structures including the tooth and supporting alveolar structure, disease identification like periodontitis and for other treatment modalities like Root Canal treatment and hence help in treatment planning strategies. Segmentation using manual method for IOPA is very complicated, laborious and time consuming and retrieving and segmenting these x rays from a huge database is very cumbersome. Here, we propose a three-step procedure for the segmentation of every individual tooth, where, first off, preprocessing is finished by employing a median filtering and then we utilize K means clustering with morphological operations which are utilized to separate the tooth structures from the Dental X-ray pictures. Performance analysis is concluded from the analysis of 10 periodical X-ray pictures and we were able to see that the accuracy of the strategy is around ninety seven percent.

**Keywords** - Intra Oral Periapical Dental X ray images, Classification, K-means clustering, GLCM, Root Canal.

## I.INTRODUCTION

The speciality of dental practice are increasingly using IOPA for the diagnosis and treatment strategy planning of dental problems especially those related to the structural damage like caries and fractures. These diagnostic xrays include IOPA, RVG, CBCT and this leads to difference in resolution, noise, background, contrast, opacity and luminance. These usually are taken to diagnosis dental caries, bone loss, fracture lines and fractures in the tooth and in diagnosing of inter proximal caries , infected pulp or periapical infection and cysts and also during the treatment of RCT. Segmentation of these xray images are also useful in forensic odontology where the identity of a person who is dead caused due to criminal intent and or natural calamities can easily be identified using these images by age estimation, dental fillings, dental treatments done and number of teeth present etc. During Forensic analysis, forensic scientist usually compare size, shape and structure and the placement of the tooth to identify a person, since the dental pattern, bite mark, occlusion, fillings and treatments on the tooth, cracks, fissures and fractures in the tooth structure, crown root length, anatomical and morphological shape, root curvature and length are as individualized as fingerprint and no two person would have the same anatomical similarities.

In this research paper, we are using the Intra Oral Periapical Xrays (IOPA) , where the iopa film is placed in the mouth against the dental structure and an x ray is passed to register the complete information with regard to the dental structure, which registers the tooth structure, underlying carious regions, the supporting bony coverage and any peri apical pathology. It provides elaborate information about the formation and stages of the growth of the tooth bud and tooth structure, root formation and root completion of teeth, the growth phase and maturity level of the jaws and the surrounding soft tissues present around the tooth and information as to whether or not any malady or disease is present or is developing or not. The biggest disadvantage if iopa is the existence of unwanted noise and illumination deficiencies which causes problems in the proper diagnosis of the disease. Segmentation of various parts of the tooth is used for various functions and goals. It can be used to identify an individual during mass disaster after post-mortem is conducted.

## II. RELATED WORKS

P.L. Lin et al., who proposed a classification using bite wing radiographs. A.K. Jain et al., suggested a contour based shape extraction method for human identification using dental xray. But the used algorithm does not analyze and detect the overall shape of the dental anatomical structure and the IOPA images are of very low contrast and are in ineffective due to blurring. E.H. Said et al. mathematical morphology is the scheme proposed here, where in the basic stages, the quality of the image is increased based on filtering algorithm and then subsequently analysis brings the end

result. O. Nomir et al., X rays taken before the death and after the death of the individual is used to identify the individual in a natural disaster situation. A method for enumerating the number of missing tooth and available tooth with the help of iopa is given by F. Aeini et al., and J. Zhou et al., proposed an active contour model to differentiate between the maxillary and mandible structure and identify the tooth. P. Lira et al., proposed a segmentation technique for dental X- rays. His study was based on supervised learning approach recognitionof the individual features of the dental structures are carried out by means of computing moments and features of statistics

## III. PROPOSED METHEDOLOGY

The proposed process flow diagram is shown in the Fig.1. Initially, pre processing is carried out using median filtering, and this processed image is then clustered by using k means clustering to segregate the image and the dental structures, and subsequently feature operations are then used to refine the results and to get the final output. Then finally KNN is used to classify the output.

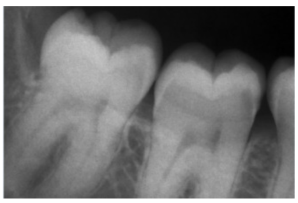


***Fig.1***

***(a)Teeth(without any problem) (b)Teeth(with problem)***

### 3.1 Preprocessing

Preprocessing is very useful to achieve the fine segmentation, because dental X-ray images always suffer from unwanted noise, low illumination. Median filtering is used to enhance and visualize the more valuable information from the dental X-rays and this filtering takes care of the noise and low illumination problems and it improves the contrast of the taken image by acting like a high filter.

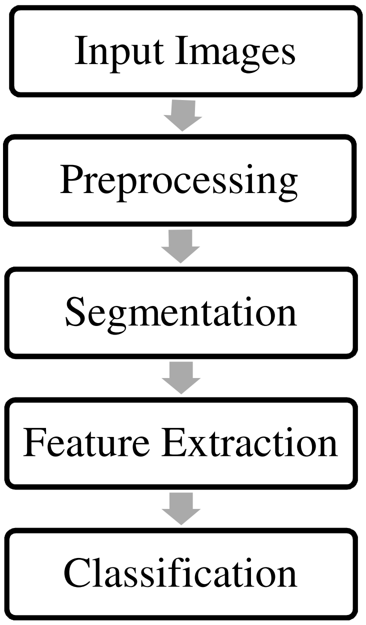


***Fig. 2 Process Flow***

Median filtering acts just like its name suggests. The median filter is normally used to reduce unwanted noise in an image, quite similar to the mean filter. But, the median filter does a better job in comparison to the mean filter at the job of preserving the accuracy and minor details in the image. This class of filter belongs to the class of edge preserving smoothing filters which are non-linear filters. This means that for two images A(x) and B(x):

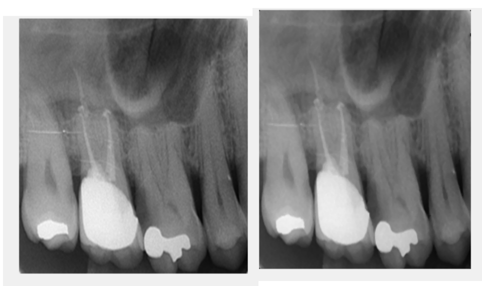

***Fig.3***
***Original Image*** ***After Preprocessing***

These filters smooth the data while keeping the details small and sharp.

 

$$median[A(x) + B(x)] \neq median[A(x)] + median[B(x)]$$

The median depicts the middle value of all the values of the pixels in the image and should not be confused with the average or Mean. The median has one half of the larger values in the whole image and also one half of the smaller value. The median is a stronger "central indicator" than the mean. The median is unaffected by a discrepant values among the pixels of the image present.

### 3.2 K-Means Clustering

K-means is a technique of clustering which divides a set of observations so as to minimize the within cluster sum of squares (WCSS). The evaluating function for an image a (m, n) is given as:

$$C(i) = Arg\ min|mx_{y^2} - nx_{y^2}|x^2$$

Where i is the no. of clusters in which the image is to be partitioned

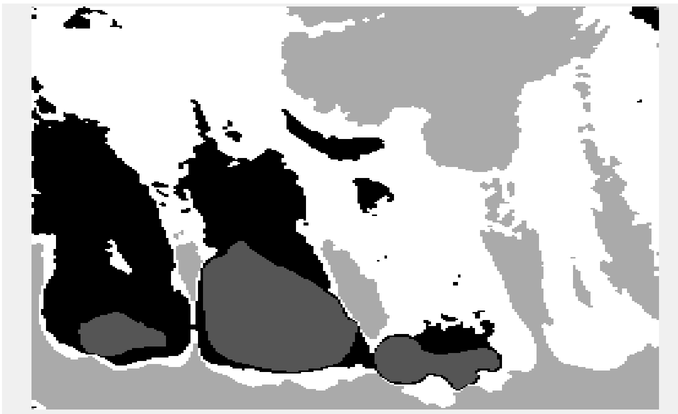

*Fig.4 Clustering Images*

In the segmentation procedure, dental X-ray pictures consist of three different regions, which comprises principally of background, teeth and bone structure and space round the teeth. The bright grey scale values indicate the tooth region, middle scale of gray values shows the bone region and the background is marked out by the dark region. The goal of the projected segmentation is to search out the contour of each individual tooth and find out the disease or abnormalities within the dental X-ray pictures

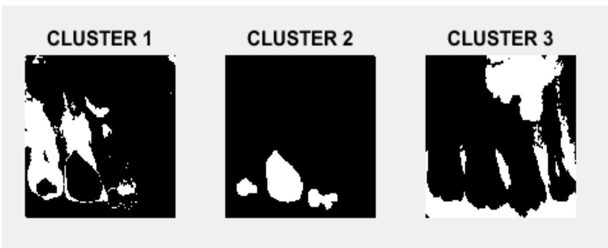


*Fig.5 Three level of Clustering*

### 3.3. Feature extraction

Feature extraction initially arises as data from information provided and slowly climbs to build up values which are representative of the whole equation which leads to more learning and subsequent generalization and thus leading to better outcomes.. Feature extraction is related to dimensionality reduction of the input processes.

An algorithm becomes redundant if the date which is given in the form of input is too big (e.g. If the inputs are both in inches and centimetre, or the repetetion of images multiple times), which then can be transformed into a set of features ( feature vector). Feature selection is the derivation of set of initial features. The selected features are a representative to contain the relevant information from theinput data, and hence contain all the relavant input data of the whole set and hence is able to perform as if all the the whole data is being utilized. And hence acts as a reduced representative of the whole set.

#### 3.3.1 GLCM Feature Extraction

The Gray Level Co-occurrence Matrix (GLCM) is used for image analysis. Given an image composed of pixels each with an intensity (a specific gray level), the GLCM is a tabulation of how often different combinations of gray levels co-occur in an image or image section. Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity at the pixel of interest.

##### 3.3.1.1 Algorithm

The feature is created in the following

- Let $s$ be the sample in the calculation.
- Let $W$ be the set of samples surrounding the sample $s$ which fall within a window centered upon sample s of the size specified under Window Size.
- Considering only the samples in the set $W$, define each element $i$, $j$ of the GLCM as the number of times two samples of intensities $i$ and $j$ occur in specified Spatial relationship (where $i$ and $j$ are intensities between 0 and Numberof levels-1). The sum of all the elements $i, j$ of the GLCM will be the total number of times the specified spatial relationship occurs in $W$.
- Make the GLCM symmetric: Create a copy of the GLCM and to this copy add the GLCM itself. This union creates a symmetric matrix in which the relationship of $i$ to $j$ is indistinguishable for the relationship of $j$ to $i$ (for any two intensities $i$ and $j$). As a consequence the sum of all the elements $i, j$ of the GLCM will now be twice the total number of times the specified spatial relationship occurs in $W$ (once where the sample with intensity $i$ is the reference sample and once where the sample with intensity $j$ is the reference sample), and for any given $i$, the sum of all the elements $i, j$ with the given $i$ will be the total number of times a sample of intensity $i$ appears in the specified spatial relationship with another sample.

 

### 3.3.2 Shape Feature Extraction

- Descriptor is nothing but the feature values. Shape descriptors can be classified by their invariance with respect to the transformations allowed in the associated shape definition. Many descriptors are invariant with respect to congruency meaning that congruent shapes will have the same descriptor.
- Another class of shape descriptors is invariant with respect to isometric. These descriptors do not change with different isometric embedding of the shape. Their advantage is that they can be applied nicely to deformable objects as these deformations do not involve much stretching but are in fact near-isometric. Such descriptors are commonly based on geodesic distances measures along the surface of an object or on other isometric invariant characteristics such as the Laplace-Beltrami.
- There are other shape descriptors, such as graph-based descriptors like the medial axis that capture geometric and/or topological information and simplify the shape representation but cannot be as easily compared as descriptors that represent shape as a vector of numbers.

### 3.4 Classification using K Nearest Neighbours

In machine learning, the KNN binary (as two class) is given more accurate data classification which beneficial to select k as an odd number which avoids the irregular data. The KNN procedure is the technique in ML procedures that's maximally distant from the two categories, by suggests that of a hyper plane. The two categories are denoted by 1 and -1.

$$c(x) = \begin{cases} 1 & if xw' \geq 0 \\ -1 & if\ xw' < 0 \end{cases}$$

It is an object which classified through a mainstream selection of its neighbours, with the determination assigned occurrence for most mutual class amongst its k nearest neighbours (k is a positive integer, classically small). Classically Euclidean distance is used as the distance metric; however, this is only suitable for endless variables. KNN is a new process that deliveries all available cases and categorizes novel cases built on an evaluation quantity (e.g., distance functions). KNN procedure is identical simple. It works built on a minimum distance from the interrogation instance to the training samples to regulate the K-nearest neighbours. The information for KNN procedure contains numerous attribute which will be used to categorize. The information of KNN can be any dimension scale from insignificant, to measurable scale.

**3.4.1 Initialization:** It is important to achieve convergence. We use the Xavier initialization. With this, the activations and the gradients are maintained in controlled levels, otherwise back-propagated gradients could vanish or explode.

**3.4.2 Activation Function:** It is responsible for non-linearly transforming the data. Rectifier linear units defined as

$$f = \max(0, x)$$

And were found to achieve better results than the more classical sigmoid, or hyperbolic tangent functions, and speed up training. However, imposing a constant 0 can impair the gradient flowing and consequent adjustment of the weights. We cope with these limitations using a variant called leaky rectifier linear unit that introduces a small slope on the negative part of the function. This function is defined as

$$f = \max(0, x) - \alpha \max(0, x)$$

Where is the leakiness parameter. In the last FC layer, we use softmax.

**3.4.3 Pooling:** It combines spatially nearby features in the feature maps. This combination of possibly redundant features makes the representation more compact and invariant to small image changes, such as insignificant details; it also decreases the computational load of the next stages. To join features it is more common to use max-pooling or average-pooling.

**3.4.4 Regularization:** It is used to reduce over fitting. We use Dropout in the FC layers. In each training step, it removes nodes from the network with probability. In this way, it forces all nodes of the FC layers to learn better representations of the data, preventing nodes from co-adapting to each other. At test time, all nodes are used. Dropout can be seen as an ensemble of different networks and a form of bagging, since each network is trained with a portion of the training data.

**3.4.5 Data Augmentation**: It can be used to increase the size of training sets and reduce over fitting. Since the class of the patch is obtained by the central voxel, we restricted the data augmentation to rotating operations. Some authors also consider image translations but for segmentation this could result in attributing a wrong class to the patch. So, we increased our data set during training by generating new patches through the rotation of the original patch. In our proposal, we used angles multiple of 90, although another alternative will be evaluated.

**3.4.6 Loss Function***:* It is the function to be minimized during training. We used the Categorical Cross-entropy,

$$H = \sum_{j=voxels} \sum_{k \in classes} c_{i,j} \log(c_{i,j})$$

Where represents the probabilistic predictions (after the softmax) and is the target. In the next subsections, we discuss the architecture and training of our CNN.

## IV. EXPERIMENT AND RESULTS

In the planned methodology, periapical dental X-ray knowledge set are taken from the data base of a private clinic- Dr.Chozhan Dental Clinic, Tamilnadu.

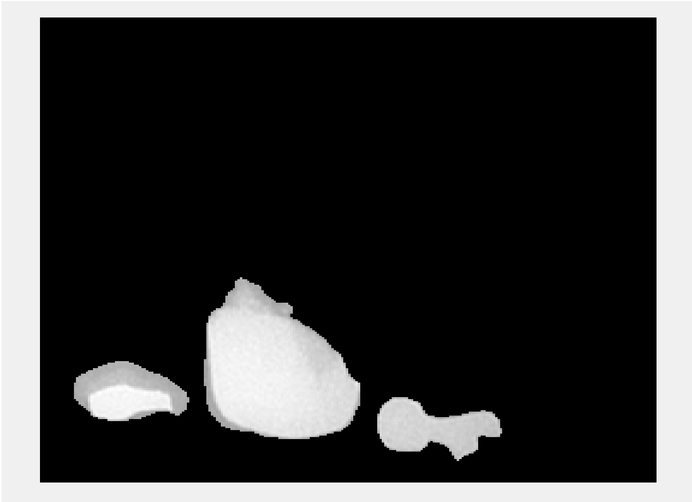

***Fig:6 Clustering Output***

From the results we can see that it contains the form of a half of a toooth,and can be seen in the above pic as a form that does not have a full form , but is less arched at its highest point, which gives the conclusion of tooth loss at that region because of Dental Caries.

## V. CONCLUSION

This paper deals with the identification of dental anomalies in the given iopa of an individual based on the shape of the segmented teeth. In the results shown, we can see that the anatomical structures of the dention and that of the bone differs dramatically and can be effectively distinguishable. This method can also be useful in the identification of an unknown person during unnatural deaths and natural calamities giving a boost to forensic odontologist and the field of forensic science. The work is an accurate diagnostic tool for a dental surgeon and forensic odontologist, in that, it is able to present the details of the dental structures and the accompanying dental anomalies in an easy and predictable fashion.

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