Detection of Inferior Alveolar Nerve Canal by Feature based Machine Learning Approach

P.Uma Maheswari¹, A.Banumathi², K.Priya³
¹,³Research Scholar, ECE, Thiagarajar College of Engineering, Madurai, India.
²Associate Professor, ECE, Thiagarajar College of Engineering, Madurai, India.

E-mail: umamahes.p@gmail.com

Abstract. For pre-diagnostic surgical process in dental implantology, detection of Inferior Alveolar Nerve Canal (IAC) in dental images is highly essential to avoid surgical complications and injury. In this paper, a feature based machine learning model is developed for the detection of IAC from the mandible regions of dental OPG images. Initially, the soft tissue regions are enhanced by S-CLAHE (Sharpening based Contrast Limited Adaptive Histogram Equalization). Subsequently, Shape features of the IAC using Histogram of Oriented Gradient (HOG) and texture features using Local Forward Rajan Transform (LFRT) are extracted. These features are considered as an input for Machine Learning classifier. From the trained results, the feature points of IAC region are detected by polynomial curve fitting approach. The performance of the classification technique is evaluated with existing machine learning classifiers. Adaboost M2 Ensemble classifier achieves the best accuracy of 96% compared to other state of art techniques such as Naïve Bayes, KNN, SVM, and Decision Tree. Therefore, the proposed method has high potential in IAC detection and avoids complexities in dental implant surgery.

1. Introduction
Dental implant is the conventional surgery fixture that is used for placing a fake root into the jawbone of the mandible region. Inferior Alveolar Nerve Canal (IAC) is one of the largest sensory nerves situated in the lower jaw that supply sensation to the mandible region. It is mandatory to detect the IAC before the surgery to avoid injury that may lead to different sensory complications. As the structure of IAC is difficult to differentiate from other soft tissue regions and it is not shown clearly in dental CT, CBCT and X-ray images is shown in Figure 1 (a) (b). So there is a need of image processing technique that gives better knowledge to delineate the IAC.

![Figure 1. Structure of IAC (Panoramic Dental OPG Image)](image_url)

Several automatic and semi automatic methods have been proposed for detecting the IAC. Sylvia et.al. proposed a active appearance model based semi automatic method for jaw tissue segmentation that detects the IAC in the 2D slice CT dental data but this method needs user intercession [1]. Sotthivirat
et.al. presented a morphological based IAC segmentation in panoramic dental x-ray images but it is not detecting the complete structure of the canal [2]. Sandhya et al. proposed foramen location detection by anatomical landmark locations [3]. Kathikeyan et al. described IAC identification by means of a statistical texture feature [4]. G Kim et al. provided an automatic extraction of IAC by volume rendering technique [5]. All these methods detect the mental and mandible foramen to locate the IAC and it may fail if the detection of foramen is inappropriate.

Histogram of Oriented Gradient (HOG) gives out excellent shape based features and Local Forward Rajan Transform (LFRT) keys can be used as a texture descriptor to locate the region from any image. Muhammed Jamshed et al. and Navnet dalal et al. presented a HOG feature descriptor for human detection [6]. Bin Li et al. proposed HOG – gist vectors as a texture descriptor for building recognition [7]. Vairaparakash proposed a well defined technique for watermarking by encrypting an image using Discrete Rajan Transform (DRT) to improve the reliability of the system and SVM classifier is used to improve the robustness and to ensure the security of the image [8]. Ekambaram Naidu Mandalapu et al. developed Rajan transform that can be used for pattern recognition tool [9]. Priya et al. proposed Rajan Transform key used as a texture descriptor [10]. So automatic method based on shape and textural analysis may provide better results compared to other state of art techniques. This paper proposed feature based algorithm that locates the IAC without detecting the foramen region.

### 2. Methodology
The dental OPG image is taken as input for extraction of Inferior Alveolar Nerve Canal (IAC). In this work, pre-processing is performed using S-CLAHE (Sharpening based Contrast Limited Adaptive Histogram Equalization). It entails uniform distribution of pixels gray level with sharpening of soft tissue regions and it enhances the image with good visual interpretation. IAC is characterized by its shape and soft tissue texture. The shape feature as HOG and texture based feature as Local Forward Rajan Transform (LFRT) are taken from pre-processed IAC region. Subsequently, machine learning based classifiers are used to classify the IAC and non IAC region from the feature values. By curve fitting polynomial function the feature points located in IAC is detected. The pipeline of this work is shown in Figure 2.

#### 2.1 Pre-processing by S-CLAHE
To reduce non uniform illumination and to highlight the IAC region, CLAHE along with sharpening filter is implemented in dental OPG images. Initially, the dental OPG images I(x,y) are divided into
non-overlapping contextual regions. Then the clip limit and the distribution parameters are used to find the cumulative distribution function to prevent image saturation [11]. For gray level distribution the clip limit is calculated with the Equation (1).

$$CL = I_{avg}^c \times N_{avg}$$  \hspace{0.5cm} (1)

where, $I_{avg}^c$ is the Average pixel in each gray level of the contextual region. $N_{avg}$ is the average number of pixel calculated for $N_x^c$ and $N_y^c$ in $x$ and $y$ direction contextual region. Then the CLAHE image $C(x,y)$ is sharpened by unsharp masking ($SC(x,y)$) procedure in which an image is sharpened by subtracting the blurred version $b(x,y)$ of the image from the CLAHE image $C(x,y)$ by Equation (2).

$$SC(x,y) = C(x,y) - b(x,y)$$  \hspace{0.5cm} (2)

2.2. Shape Feature Extraction by HOG

The shape or structure of the object is explicates by HOG feature descriptor. It identifies the object from mixed-up background without using object detection algorithm and the major advantage of using HOG is to localize the object appearance and shape within an image and can be described by the distribution of intensity gradients or edge directions. Therefore it is extremely appropriate for dental OPG image analysis. HOG is able to provide edge magnitude and direction by extracting the gradient and orientation of the edges [6]. Initially the pre-processed image is separated into 8 x 8 cells, and for the pixel within each cells, a histogram of gradient directions is computed by Equation (3) and (4).

$$HOG_g = (g_x^2 + g_y^2)^{1/2}$$  \hspace{0.5cm} (3)

$$HOG_\theta = \arctan \frac{g_y}{g_x}$$  \hspace{0.5cm} (4)

Histogram of gradient value is calculated to assign the bin value and to get the normalized histogram ($FV_{HOG}$) value. Then the maximum, minimum and mean value in that block is taken as the feature vector for classification shown in Equation (5), (6) & (7)

$$HOG_{max} = \max (FV_{HOG})$$  \hspace{0.5cm} (5)

$$HOG_{min} = \min (FV_{HOG})$$  \hspace{0.5cm} (6)

$$HOG_{mean} = \text{mean}(FV_{HOG})$$  \hspace{0.5cm} (7)

Though, the HOG gives better shape information of IAC there is a possibility of producing the same feature information for other regions such as a mandible bone. So to overcome this issue apart from using HOG, keys from LFRT are also consider as a texture feature to classify the IAC perfectly. Combination of these approaches significantly reduced the training and execution time compared to other state of art techniques.

C. Texture Feature Extraction by LFRT

LFRT texture descriptor has been used to extract the texture features of IAC from the pre-processed image. Initially, the pre-processed image input sequence ($X$) is taken as 3 x 3 matrixes by taking 8 neighborhood of each center pixel (M). Then divide each 8 neighborhood pixel into two halves each consisting of M/2 points. Further divide that values into M/4 sections and continue this process till no more division is available. The total number of stages comes for each 8 neighborhood to be $\log_2M$. The transform function ($A_M$) obtained by operating the Rajan Transform Martix ($RT_M$) with the input matrix 3 x 3 ($X_{Mx1}$) is depicted in Equation (8)

$$A_M = RT_M \times X_{Mx1}$$  \hspace{0.5cm} (8)

RT$_M$ matrix is created by Identity matrix(I) and encryption key ($e_k$) shown in Equation (9&10) and encryption key is generated (Equation 11) by comparing two input values in the input sequence.
where \( RT_M = \begin{bmatrix} I_M \bar{e}_k \bar{I}_M \\
\bar{e}_k \bar{I}_M 
\end{bmatrix} \)  
\( e_k = (-1)^k \)  
\[ k = \begin{cases} 1 & \text{for } x(\frac{i + M}{2}) < x(i); \: 0 < i < \frac{M}{2} \\
0 & \text{Otherwise} \end{cases} \]

\( RT_M \) matrix (8 x 8) created for the first input sequence 8 x 1 with the generated key value is shown in Equation (12).

\[
RT_M = \begin{bmatrix}
1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\
-1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & -1 & 0 & 0 & 0 & -1 & 0 & 0 \\
0 & 0 & -1 & 0 & 0 & 0 & -1 & 0 \\
0 & 0 & 0 & -1 & 0 & 0 & 0 & -1 \\
\end{bmatrix}
\]

LFRT is produced by taking the decimal value of the last encryption key is presented in Equation (13)

\[ LFRT_M = D(e_{log2M}) \]

**D. Adaboost M2 Ensemble Classifier**

It is a multiclass learning algorithm to train multiple models with weak learners. This classifier minimizes the factors like noise, bias, variance and thereby improves the stability and predictability. It guarantees to achieve better accuracy by reducing the error rate less than \( \frac{1}{2} \). Here the learning set consist of IAC and non IAC images in training data (\( y_{12} \) & \( y_{22} \)) and validation set is \( z_{12} \) (IAC Images) and \( z_{22} \) (non IAC Images) with the classification group (G). Initialize weight vector by Equation (14) for the weak learner (h) in the training dataset with the distribution in Equation (15)

\[ w_{i,t}^k = \frac{1}{N|G|-1} \]

\[ D_t(i) = \frac{w_i^t}{\sum_{i=1}^N w_i^t} \]

Then calculate the error rate by Equation (16) for each weak classifier and pick classifier with the lowest error rate

\[
E_t = \frac{1}{2} \sum_{i=1}^N D_t(i)(1 - h((x,y),G)) + \frac{1}{|G|-1} \sum_{g \neq G} h((x,y),G))
\]

Subsequently, compute the voting power for the classifier appends it in ensemble classifier until it classifies good.

**E. IAC Detection using Polynomial Curve Fitting**

IAC is detected by 3rd order polynomial function to exactly fit the data points that locates the IAC completely. The polynomial equation is shown in (17)

\[
f(x) = p_n x^n + p_{n-1} x^{n-1} + \ldots + p_1 x + p_0
\]

where \( n \) is the polynomial degree, \( p \) is the row vector of polynomial coefficients and \( x \) is the feature points value classified by the Adaboost M2 ensemble classifier to detect the IAC.
3. Results and Discussion

The 180 samples of dental OPG images are collected from CSI College of dental science and research, Madurai as shown in Figure 3(a) and 3(b). The input images are resized to 250 x 450 as shown in Figure 4 and the sample image 3(a) is enhanced by S-CLAHE to sharpen the IAC region effectively. Matlab R2018b and Windows 7 (64 bit) is used for experimentation.

After pre-processing, eight region of interest (ROI) images are taken for IAC and non IAC region from each input image with the size of 50 x 50. From that, 720 images are selected for IAC and 720 images are selected for non IAC region. IAC is mainly categorized by its shape and soft tissue texture, so it has to be analyzed by both of its characteristics and that is done by HOG and LFRT. From each ROI, the maximum, minimum and mean value of HOG shape feature and the decimal key value of LFRT is extracted as a feature vector in the size of 1 x 52. 1440 images were separated into two exclusive sets, 80% is used for training and 20% is used for testing and it is evaluated by different machine learning classifiers.

Adaboost M2 Ensemble classifier achieves better accuracy of 96% by considering weak hypothesis for classification and reduces the error rate less than ½. Table 1 shows the accuracy, recall, precision and F1 score computed for the use-case of ensemble classifier for HOG and Rajan Transform Key feature values taken for 1440 images.
Table 1. Accuracy – Adaboost M2 Ensemble classifier

| Total Images | Class | Features         | Classifier         | Precision | Recall | F1 Score | Accuracy (%) |
|--------------|-------|------------------|-------------------|-----------|--------|----------|--------------|
| 1440         | Nerve (IAC) | HoG + LFRT key | Adaboost M2 Ensemble | 100       | 92.3   | 96.00    | 96           |
|              | Non Nerve |                  |                   | 91.66     | 100    | 95.6     |              |

The analysis shows Adaboost M2 Ensemble classifier provides excellent classification compared with other machine learning classifiers as shown in Figure 5.

![Accuracy comparison of Adaboost M2 Ensemble classifier Vs Machine Learning Classifiers.](image)

**Figure 5.** Accuracy comparison of Adaboost M2 Ensemble classifier Vs Machine Learning Classifiers.

With the help of classified IAC features, the input image IAC region features are taken separately and given to the third order polynomial curve fitting approach to detect the IAC. It detects the left and right region of IAC and that is shown in Figure 6 (a) (b). Extracted IAC is compared with the ground truth image and gives out an average distance error of 0.82.

![IAC detected region in dental OPG image( Left and Right)](image)

**Figure 6.** IAC detected region in dental OPG image( Left and Right)
4. Conclusion
HOG and LFRT feature based machine learning classifier model proposed for automatic detection of IAC region in dental OPG images. Pre-processing by S-CLAHE technique is utilized here to enhance the IAC region. HOG and LFRT key feature is taken as shape and texture feature to classify the features of IAC and other regions in dental image. After the feature extraction, Adaboost M2 Ensemble classifier model classifies the IAC in a better way compared to other machine learning classifiers and it achieves 96% of accuracy. The polynomial curve fitting approach locates the IAC by nerve regions features classified by Ensemble classifier model. When examined with ground truth image, it is perceived that the feature based model gives best solution to locate the position of IAC with minimum error. This algorithm is exceptionally recommended for IAC detection in dental OPG image to avoid the IAC injury and other complexities in Oral surgery and Dental Implantology.

Acknowledgment
This research work is supported and funded by the Council of Scientific & Industrial Research (CSIR) - Human Resource Development Group (SRF File no.: 08/237(0015)/2018-EMR-I).

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