Performance Analysis of Dental Deformities in Cephalometry Image Using Soft Computing Technique

K RAMYA[1], DR.A. BANUMATHI[2]

1 PG Scholar, Department of Electronics and Communication Engineering, Thiagarajar College of Engineering, Madurai

2 Associate Professor, Department of Electronics and Communication Engineering, Thiagarajar College of Engineering, Madurai

Abstract- This paper proposes an automated target classification algorithm using Soft Computing Technique to extract feature vectors for craniofacial features in cephalometric radiograph. The proposed work is based on image segmentation and classification technique, using Top-Hat filter and soft computing technique. The pre-processing includes Histogram Equalization [HE] to improve the contrast level. The pre-processed image is then segmented for image analysis. Segmentation will extract small elements and details. The features are extracted by subjecting the radiography to the Gray Level Co-occurrence Matrix [GLCM] algorithm. The resultants are the frontend of support vector machine. Vectors, which posse's landmarks, are separated from all other vectors. The centroid points, automatically determined from GLCM feature vectors, are the location of landmarks. The landmark points which are serving as a guide for construction and measurement of planes. The resultant segmentation, are the frontend of Convolutional Neural Network [CNN], classifies the normal cephalometric dental image into abnormal cephalometric dental image. According to the performance evaluation of SVM, accuracy and sensitivity of the classification were automatically estimated using True Positive [TP], False Positive [FP], False Negative [FN], and True Negative [TN]. The accuracy of CNN is, number of correct predictions divided by total number of predictions. Finally results of the classification, which has 92.6% accuracy for Non-linear kernel and 70% accuracy for linear kernel of SVM and CNN classifier, gives 78.01% accuracy. The performance measurement of soft computing, are used to evaluate the dento-facial relationship, study of growth and development, and also for treatment planning.

I. INTRODUCTION

This project proposes an automated target classification algorithm using soft computing technique to extract landmark points and find the abnormalities from craniofacial features in Cephalometry radiograph. Facial deformity affects the jaw and dentition. This deformity is mainly seen in various facial syndromes like apert, crouzon, and treacher Collin's syndromes, cleft lip and hypertelurism. Dento-facial deformities do not appear instantaneously, but arise during an individual's growth, as facial and jaw relationships are modified continuously under the combined influence of genetic controls and environmental conditions. The proposed preprocessing approach, histogram equalization and segmentation approach, top hat filter, the significant information is obtain from the dental input image, in order to proceed with the process of feature extraction. In feature extract stage, segmented region will be used to extract features which describe about the texture. Texture extraction is performed by GLCM (Gray Leave Co-occurrence Matrix). The texture features representing the total features and its used for proceeding with Support Vector Machine (SVM). SVM training is provided with reference samples for its normal and abnormal classification. SVM is a supervised learning model used to classify and identify the test dental image either for normal or abnormalities based on supervised training with the radial basis kernel function. In CNN (Convolutional Neural Network), has convolution layer and pooling layer and fully connected layers. At last, the simulated result shows that the utilized methodologies are providing better performance and good classification and accuracy rather than the earlier methods of the identification of the identification of dental defects.

II. LITERATURE SURVEY

Cardillo M. A. Sid-Ahmed [1] "An Image Processing System for Locating Craniofacial Landmarks" *IEEE Transactions on Medical Imaging, Vol 13, No. 2, June 1994.* In this paper a new automatic target recognition algorithm has been developed to extract craniofacial landmarks from lateral skull x-rays (cephalograms). The locations of these landmarks are used by orthodontists in what is referred to as a cephalometric evaluation. The evaluation assists in the diagnosis of anomalies and in the monitoring of treatments. The algorithm is based on gray-scale mathematical morphology. A statistical approach to training was used to overcome subtle differences in skeletal topographies. Decomposition was used

III. PROPOSED SYSTEM

A block diagram of a typical system for the diagnosis of dental deformities in a cephalometry image is shown in Figure 1.2. The cephalometry image is pre-processed to sharpen the edges of various bones in the lateral view of the face. Edge sharpening in cephalometric image is achieved through a histogram equalization process. The edge features are then extracted from the enhanced cephalometric image. The extracted features are classified as landmark and non-landmark points using Support vector machine technique. Finally angle between various landmark points are calculated to find out the deformities in the dento-facial growth.

- Methodology:
- Preprocessing:

The first step is to provide a better visualization to help the orthodontist in labeling cephalometric points. Histogram equalization is used to improve the quality of the image. The Histogram equalization is used to enhance contrast. The histogram equalized image is divided into sub-images, to simplify the further processing.

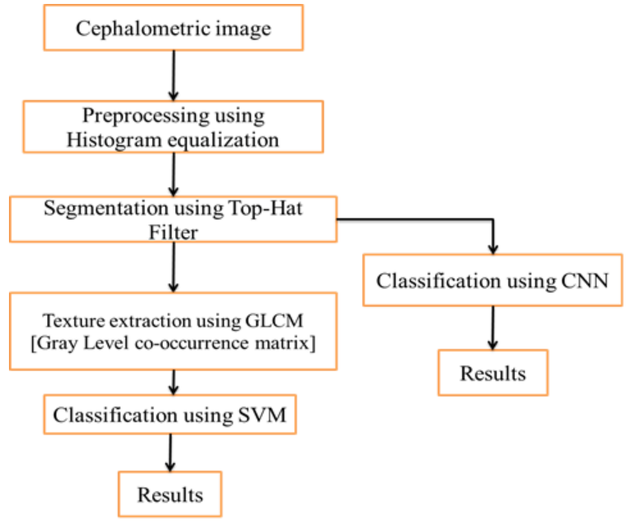


Fig. 1 Block diagram of proposed methodology

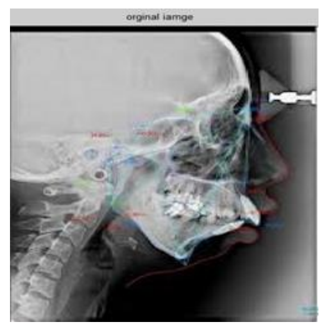


Fig. 2 Input lateral Cephalometry image

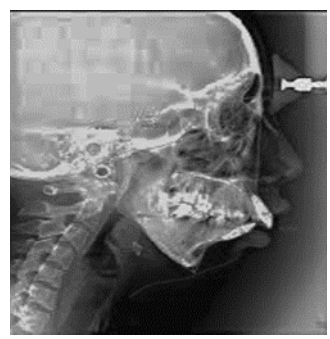


Fig. 3 Preprocessed image

Since medical image data are massive in quantity, there is a compelling need to generate one-dimensional array of numeric values representing the characteristic features of the pre-processed image.

- Segmentation:

Top-Hat Filter is a mathematical morphology and digital image processing, top-hat transform is an operation that extracts small elements and details from given images. Two types of Top-Hat filter present, white top-hat and black top-hat filter. The mathematical functions are

- $T(f) = f - f \circ b$
- $f \circ b = (f \ominus b)\ b$

for white top-hat and

- $T(f) = f - f \cdot b$
- $f \cdot b = (f\ b) \ominus b$

for black top-hat filter

Fig. 4 White Top-Hat image

- Feature extraction using Gray level co-occurrence matrix [GLCM]:

A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix [13]. The GLCM functions characterize the texture of an image by calculating how often pairs of pixels with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical

measures from this matrix. *Energy:* It is also known as uniformity or the angular second moment. It returns the sum of squared elements in the GLCM. It is defined for an image C as follows

$$Energy = \sum_{i,j=1}^{N} {C_{ij}}^2$$

Energy is 1 for a constant image.

Contrast: It measures the local variations in the gray-level cooccurrence matrix. It returns a measure of the intensity contrast between a pixel and its neighbor over the whole image.

$$Contrast = \sum_{i,j=1}^{N} (i-j)^2 {C_{ij}}^2$$

Contrast is 0 for a constant image.

Correlation: It measures the joint probability occurrence of the specified pixel pairs. It returns a measure of the intensity contrast between a pixel and its neighbor over the whole image.

$$Correlation = \frac{\sum_{i,j=1}^{N} (i-\mu i)(j-\mu j){C_{ij}}^2}{\sigma_i \sigma_j}$$

Correlation is 1 or −1 for a perfectly positively or negatively correlated image. *Homogeneity:* It measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Homogeneity is 1 for a diagonal GLCM. It is defined as

- Classification:

SVM Classification:

These GLCM vectors are the front-end for the support vector machine (SVM). The support vector machine is trained with the GLCM vectors. Once trained, the SVM will be able to discriminate the landmark vectors from non-landmark vectors during testing. The vectors from GLCM technique are mapped into high dimensional feature space by Radial Basis Function (RBF) kernel of SVM, where a maximal margin hyper plane can be found linearly the one that separates the training data. The relevance of such high dimensional feature processing is evident, where extraction of non-linear features from training images is much easier through SVM, especially those which are harder to identify using human cognition. The basic nature of classification with an SVM can be illustrated most easily for the simple situation in which there are two nonlinearly separable classes in high dimensional space. Using the training data represented by, {xi, yi}, i=1,2,….,r, yi∈{1, −1} in the high dimensional space, a

$$Homogeneity = \sum_{i,j=1}^{N} \frac{C_{ij}}{1+|i-j|}$$

Image-I Image-II Image-III Image-IV

Fig.5 sample images for top-hat filter

Feature	Image-I	Image-II	Image-III	Image-IV
Contrast	0.9499	0.4863	0.5643	0.5152
Correlation	0.8993	0.9142	0.8594	0.8980
Energy	0.2291	0.3754	0.4050	0.3451
Homogeneity	0.8687	0.8840	0.9173	0.8738
Mean	71.28	41.74	36.26	39.79
Standard Deviation	76.23	57.49	50.72	54.02

Table 1 GLCM Feature Vectors

classifier is developed which generalizes accurately. Many hyper planes could be fitted to separate the class but, there is only one optimal separating hyper plane, which is expected to generalize well in comparison to other hyper planes. This optimal hyper plane should run between the two classes with all cases of a class located on one side of the separating hyper plane. This plane itself is located such that the distance to the closest training data points in both of the classes is as large as possible. The proposed method uses binary SVM that minimizes the following objective function with dual coefficients α_i

$$\min_{\alpha} : \frac{1}{2}\sum_{i,j}\alpha_i(Q_{i,j}+\frac{8\gamma}{C_i}\delta_{i,j})\alpha_j - 4\gamma\sum_i \alpha_i$$

Subjected to: $\Sigma y_i\alpha_i = 0$ and $0<=\alpha_i<=c_i$, where $\gamma i=2\log 2$ defines the margin of separation between two classes, αi is the Lagrangian multipliers and Ci are data dependent regularization parameter, which controls the tradeoff between complexity of the machine and the number of nonseparable points. Both γ and Ci are obtained by tuning the performance of Gini SVM on a cross validation set. $\delta ij=1$ for i=j and zero otherwise Qij= yiyj k(xi; xj) is the kernel evaluated at training vectors 'i' and 'j', here, xi are training vectors, yi=±1 are the corresponding class labels, and k (xi; xj)==exp(-||xi-xj||^2) is Radial basis kernel (RBF) Lagrangian multipliers αi are evaluated by solving the quadratic Eq. (3). The training vectors xi, whose corresponding αi is nonzero, are called support vectors. When the above optimization problem is solved, an optimal hyper plane in a high-dimensional feature space can be obtained to separate the two-class samples. Accuracy and sensitivity of the landmark points located were automatically estimated using true positive (TP), True negative (TN), False positive(FP) and false negative (FN).

Fig.6 a) Training image for reference.
b) Test image

Sensitivity = TP/ (TP+FP)

Accuracy = TP+TN/(TP+FP+FN+TN)

The FN being the false negatives, the landmark is classified as non-landmark and with TN being the true negative, non-landmark is correctly classified. True positive and false positive are defined as landmark classified as land mark and non-land mark classified as land mark.

MODEL	ACCURACY
SVM (Radial Basis Function) Classification	92.6%
SVM (Linear) Classification	70%
TREE Classification	45%
NAÏVE BAYES Classification	65%

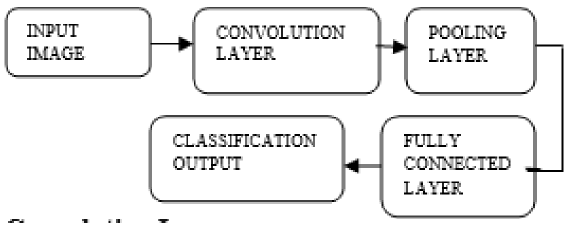
Table 2 Accuracy Measurement

MODEL	SENSITIVITY
SVM(Radial Basis Function) Classification	94%
SVM (Linear) Classification	75%
TREE Classification	53%
NAÏVE BAYES Classification	67%

Table 2 Sensitivity Measurement

- CNN classification:

A CONVOLUTIONAL NEURAL NETWORK (CNN) is a Deep Learning algorithm which can take an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. Convolution neural network classifies the Normal Cephalometric Image and abnormal Cephalometric Image.



- Convolution Layer:

A convolutional layer contains a set of filters whose parameters need to be learned. The height and weight of the filters are smaller than those of the input volume. Each filter is convolved with the input volume to compute an activation map made of neurons.

- Pooling Layer:

Pooling layers are generally used to reduce the size of the inputs and hence speed up the computation. Consider a 4 X 4 matrix as shown below: Max pooling and Average pooling.

- Fully Connected Layer:

The output layer in Convolutional neural network (CNN) is a fully connected layer, where the output feature maps of the final convolution or pooling layer is typically flattened, i.e., transformed into a one-dimensional (1D) array of numbers (or vector), and connected to one or more fully connected layers. It classifies the input pattern with high level features extracted from convolution layer and pooling layer.

```
Epoch 1/10
157/157 [==============================] - 76s 483ms/step - loss: 1.7718 - accuracy: 0.3406 - val_loss: 1.4024 - val_accuracy: 0.4871
Epoch 2/10
157/157 [==============================] - 75s 481ms/step - loss: 1.3474 - accuracy: 0.5089 - val_loss: 1.2191 - val_accuracy: 0.5628
Epoch 3/10
157/157 [==============================] - 76s 481ms/step - loss: 1.1923 - accuracy: 0.5714 - val_loss: 1.2312 - val_accuracy: 0.5682
Epoch 4/10
157/157 [==============================] - 76s 481ms/step - loss: 1.0614 - accuracy: 0.6255 - val_loss: 1.0626 - val_accuracy: 0.6212
Epoch 5/10
157/157 [==============================] - 75s 479ms/step - loss: 0.9710 - accuracy: 0.6568 - val_loss: 0.9995 - val_accuracy: 0.6428
Epoch 6/10
157/157 [==============================] - 75s 480ms/step - loss: 0.8994 - accuracy: 0.6840 - val_loss: 0.9806 - val_accuracy: 0.6642
Epoch 7/10
157/157 [==============================] - 80s 508ms/step - loss: 0.8195 - accuracy: 0.7111 - val_loss: 0.9141 - val_accuracy: 0.6811
Epoch 8/10
157/157 [==============================] - 75s 480ms/step - loss: 0.7601 - accuracy: 0.7329 - val_loss: 0.9584 - val_accuracy: 0.6754
Epoch 9/10
157/157 [==============================] - 75s 480ms/step - loss: 0.6974 - accuracy: 0.7539 - val_loss: 0.8660 - val_accuracy: 0.7043
Epoch 10/10
157/157 [==============================] - 75s 480ms/step - loss: 0.6230 - accuracy: 0.7801 - val_loss: 0.8760 - val_accuracy: 0.7075
```

Fig.7 CNN Classification

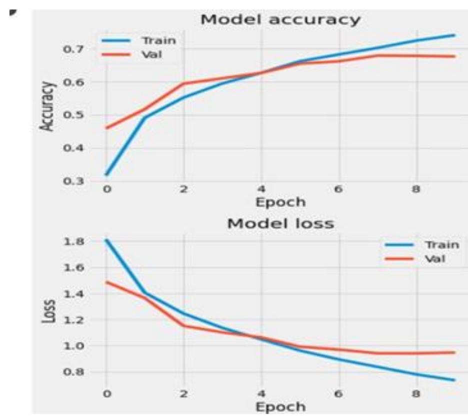


Fig. 8. Accuracy and loss measurement.

The Accuracy of training is 78.01% and accuracy of validation is 67.11% and the total number of epochs is ten and training time is 12 min 8 sec for two classes. The no. of training samples is 157 and validate samples is 50.

IV. RESULTS

The lateral cephalogram images are digitized to an average size of 256×256 pixels as shown in Fig. 2.

Hundred images are taken for training. To make the edges discriminable, both the training and testing images are globally edge enhanced by histogram equalization to increase the dynamic range as shown in Fig. 3.

The pre-processed image is divided into Top-Hat transmission image as shown in Fig. 4

In the GLCM process, four 64×64 edge flag maps are generated. They are called as feature maps. The median value taken from the edge intensities of the image is considered as the threshold value for edge detection and also to eliminate the noise. Finally, a vector is formed by series-connecting the all-feature vectors are shown in Tabel.1. Similarly, standard deviations in every four rows are calculated.

Out of these 64 vectors, only those vectors which are Out of these 64 vectors, only those vectors which are part of the edges have larger gray value. During the training of support vector machine, the GLCM vectors corresponding to landmark points and non-landmark points are given as input in binary form. The SVM is trained using 4,096 (16× 64×4) GLCM vectors. The choice of the RBF classifier is motivated by the fact that it is a kernel-based method depends on a statistical criterion for defining the discriminant hyper plane in the transformed kernel space. The naïve Bayes classifier, which is a reference classification method for land mark identification, is used. Evaluation of the recognizer is performed by scanning the test images pixel by pixel 64×64 pixels of 16 frames are extracted. Figure 6a shows the image with the landmark points for training. From the training image set, the support vectors are generated. The training image and test image considered for this study visually show retrognathic mandible and protrusive maxilla in nature which are shown in Fig. 6a and b. The GLCM vectors for the test image are generated for all the frames and class conditional probabilities for the test image are computed. These probabilities are obtained using kernel function that compares each vectors of the test image with the support vectors gained from the training set. The landmark location estimate is chosen from the frame with the highest-class conditional probability out of all frames in an image. The landmark points, which are located in test image, are estimated with centroid co-ordinates and is shown in Fig. 6b. The implementation of the proposed methodology is done using MATLAB. Tables 2 and 3 show the performance comparison of accuracy and sensitivity of the proposed method with the existing SVM and a Naïve Bayes classifier for various landmark points. The proposed SVM classification is more accurate than the other two classification techniques. The accuracy of the classification produced by any classifier is positively related to training set size. In the proposed method with SVM, the classification is effective even with minimum number of training set due to the standard deviation which is the additional parameter included for accurate training. In CNN Classification results are shown in Fig. 7.

Accuracy and loss measurement are shown in Fig. 8.

CONCLUSION

An automated diagnosis of dental deformities is proposed in this paper. The Gray Level Co-occurrence Matrix vector features along with Support Vector Machine classifier are utilized for the task of cephalometric landmark identification. The accurate location estimation of the landmark is obtained using the recognizer, which is as good as the performance of the expert dentists for a similar task. On an average, 92% accuracy for SVM and CNN gives 78.01% accuracy. It is evident that from the Table 2 and 3, the proposed method reduces the requirement of number of images in the database and in turn increases the speed, as mean and standard deviation are taken as the input vectors for the Gini SVM. The measured performance will assist the dentist to quickly arrive at a conclusion whether a patient has been affected by any dental deformities or not.