Numbering and Classification of Panoramic Dental Images Using 6-Layer Convolutional Neural Network

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Abstract—Deep Convolution Neural Network is one of the most powerful tools to solve complex problems of image classification, image recognition, financial analysis, medical diagnosis and many similar problems. A dental panoramic image consists of collection of teeth of both upper jaw and lower jaw. Automatic classification of dental panoramic images into various tooth types such as canines, incisors, premolars and molars has been a challenging task and involves crucial role of an experienced dentist. In this paper, we propose a technique for numbering and classification of the panoramic dental images. The proposed algorithm consists of four stages namely pre-processing, segmentation, numbering and classification. The pre-processed panoramic dental images are segmented using fuzzy c-mean clustering and subjected to vertical integral projection to extract a single tooth. The image dataset consists of 400 dental panoramic images collected from various dental clinics. The 400 dental images are divided into 240 training samples and 160 testing samples. The image data set is augmented by applying various transformations. Panoramic dental images are further numbered using a universal dental numbering system. Finally, the classification is done with the help of 6-layer deep convolution neural network (DCNN) consisting of 3 convolutional neural network and 3 fully connected network. The tooth is classified as canine, incisor, molar and premolar. An accuracy of 95% has been achieved for augmented database and 92% for original dataset with the proposed algorithm. The proposed numbering and classification of dental panoramic images is useful in biomedical application and postmortem recording of dental records. In case of big calamity, the system can also assist the dentist in recording post mortem dental record that is a very lengthy and arduous task.

Keywords: deep convolution neural network, segmentation, tooth classification

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INTRODUCTION

Teeth have a significant role in esthetics, mastication and phonetics [1]. Automated dental identification system (ADIS) has been developed to extract information from the tooth images [2]. The technique has been distinctively used for identification of unknown persons by mapping the postmortem dental record with antemortem dental record. The system leads to saving time and gives accurate result. However, the system may not be successful due to the long gap between antemortem and postmortem matching and changes in dental features. In-order to overcome these shortcomings, several works have been proposed for automation of dental tooth information from dental X-ray images for better matching between antemortem images and postmortem images [3–7].

In this paper we have used Deep Convolutional Neural Network for classification of dental images into molar, premolar, canine and incisor. According to the universal dental numbering system as shown in Fig. 2, a panoramic image consists of 32 teeth where 16 teeth are on the upper part of jaw and other 16 teeth are on the lower part of the jaw. The lower jaw is called mandible and the upper jaw is called maxilla [8]. Figure 1 portrays the panoramic dental X-ray image and Figure 2 shows the universal dental numbering system. A panoramic dental image consists of four important components namely teeth, gums, pulp, and background. The teeth are separated accordingly and the region of interest (ROIs) identified. Every tooth has crown and root, which constitute the upper and lower part of the tooth respectively.

The use of deep convolutional neural network algorithms is helpful in organizing, analyzing, and interpreting the various images [9]. CNN is comprised of several convolutional layers followed by fully connected layers in order to effectively segment the image. CNN has three distinct layers namely convolution layer, pooling layer, and fully connected layer. CNN provides an extremely good performance in analysis of medical images. Deep learning methods when employed in CNN have helped in understanding the

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Fig. 1. Panoramic dental X-ray image.

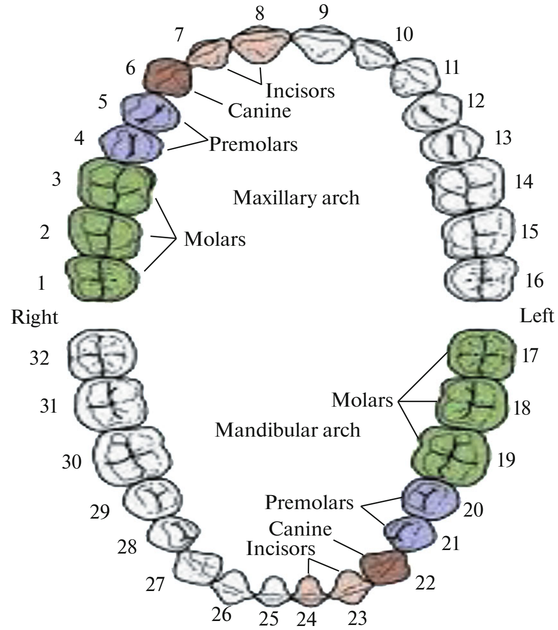

Fig. 2. (Color online) Dental numbering system.

various disease conditions in several of the medical images [10]. The method has been successful in increasing the accuracy and precision while processing medical images. The application of this algorithm on the CT images helped in identifying key features that could be used for predicting age related macular degeneration [11]. In order to classify the images and cluster them according to similarity, we require Deep Convolution neural network for more accuracy.

Hence in this work, a 6-layer Deep convolution network has been proposed to classify the type of a tooth in a panoramic image.

LITERATURE SURVEY

Automation of dental images helps in preventing the mistake caused due to human error. Tangel et al. [3], proposed a method of classification of periapical dental images by multiple fuzzy attribute. Experimental results on 78 periapical dental X-ray images showed an accuracy of 84.29%. Hosntalab et al. [4], presented the system of automation for matching postmortem and ante mortem records on bitewing dental X-ray images. Zhou and Abdel-Mottaleb [5], proposed a content-based system for identification based on bitewing of human dental X-ray images. Lin et al. [6], proposed a dental bitewing classification and numbering system of premolar and molar tooth. The segmentation of tooth was based on the relative length/width ratio. Then the numbering was done based on the dental numbering system. A total classification accuracy of 95.1% was achieved with the system. Ali et al. [7], proposed the algorithm for detection and classification of dental caries using neural network. DCNN have been used for various computer vision tasks such as image classification [12, 13] and object detection [14, 15]. Various CNN architecture for image classification include Alexnet, VGG, Googlenet, and ResNet. CNN classify the images based on optimization and regularization. The routine optimization method includes the stochastic descent gradient (SGD). The major regularization techniques include L_2 regularization, drop out, and data augmentation [16]. Analysis of images based on deep learning techniques has been a significant achievement in data analysis. Deep neural networks have a wider applicability in handling noisy datasets. Two of the most common architectures that are used in deep learning are those based on supervised training and others based on un-supervised training. Un-supervised systems utilize layer-by-layer pre-training of DNN. Examples of these include deep belief network (DBN), stacked auto encoders (SAE), and restricted Boltzmann machines (RBM). Supervised systems include end-to-end training of entire DNN. Examples include recurrent neural networks (RNN) and Convolutional neural networks (CNN). Several studies have been done using deep neural network for image classification. Zhou et al., used Alexnet Architecture [17] proposed by Krizhevsky et al. [18] for classifying the dental cone-beam computed tomography (CT) images. After data augmentation, the classification accuracy was 91%. Miki et al. [21] used Alex net architecture for classification and numbering of teeth of dental cone-beam computed tomography images. They achieved the classification accuracy of 88% without data augmentation and 91% with data augmentation. Kuo et al. [29] also used CNN for classification of dental panoramic radiography images and achieved the accuracy of 85.3%. Yu [31] proposed a 4-layer CNN model for dental panoramic images. The accuracy rate was 90%. Macho et al. [19], developed method for automatic segmentation of teeth in CT scans of the human skull. The method utilized

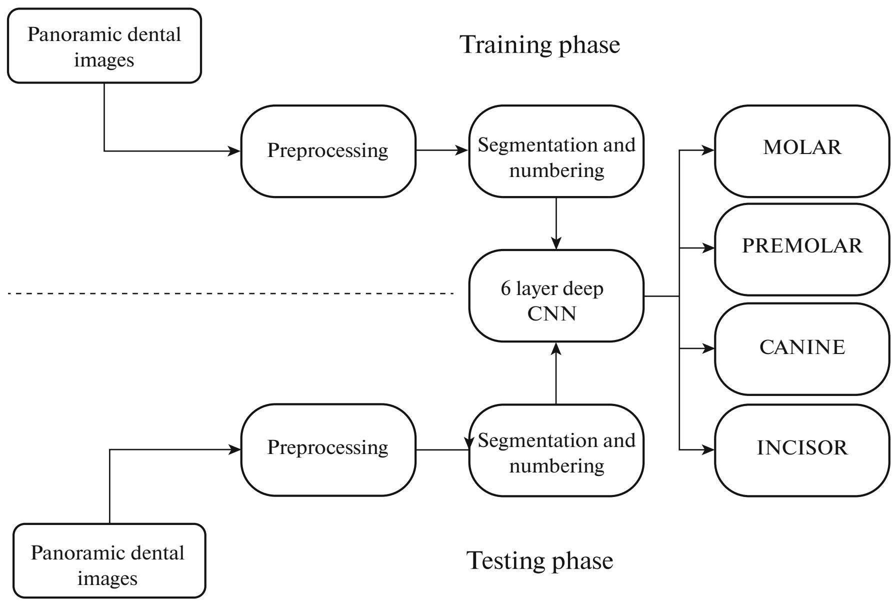

Fig. 3. Block diagram of proposed technique using 6-layer deep convolutional neural network.

CNN with 3D volumetric convolutions. A hierarchical CNN based approach was utilized to develop the automatic segmentation. The method was robust when tested on different patients. Poedjiastoeti et al., utilized a 16-layer CNN for large data set to analyze the presence of jaw tumors in dental images. The dataset consisted of 400 images. The developed method had a sensitivity of 81.8%, specificity of 83.3% and precision of 83%, respectively. The values proposed were comparable to the detection by oral and maxillofacial specialist which were 81.1, 83.2, and 82.9% [30].

In this paper, a technique has been proposed to assign number to individual tooth in panoramic dental X-ray image according to universal numbering system and then the tooth number is fed to the 6-layer deep convolutional neural network to classify it into molar, premolar, canine and incisor. The proposed technique consists of four phases: preprocessing, segmentation, numbering and classification of dental images.

PROPOSED WORK

The proposed framework for numbering and classification of panoramic dental images using 6 layer deep convolutional neural network is illustrated in the block diagram shown in Fig. 3 and is detailed in further sub-sections.

Data Preprocessing

The panoramic dental radiography X-ray images are enhanced to eliminate noise and improve contrast. This step makes them suitable for segmentation. Enhancement has been done through median filtering. The digital dental images used in this study were obtained with due courtesy from two dental clinics, namely Smart Smile Dental Clinic and Implant Centre (New Delhi, India) and North Point Dental Clinic (New Delhi, India). Figure 1 shows original panoramic image before preprocessing. The resolution of panoramic X-ray image is 1152 × 480 pixels which contains teeth, jaws, adjacent structures and maxillary sinus. The images were cropped to 286 × 286 pixels which contains teeth and jaws only. After applying median filter, we get the enhanced panoramic image as shown in Fig. 5.

Segmentation

The preprocessed images are segmented using fuzzy c-mean clustering. Segmented image after applying fuzzy c-mean clustering on Fig. 5 is shown in Fig. 6. Clustering can be identified as hard and soft clustering respectively. Fuzzy clustering is a class of soft clustering. Data in fuzzy clustering belongs to more than one cluster. It is better than the hard clustering as the objects on the boundaries between several classes do not fully belong to one class but they are given membership function between 0 and 1, which indicates the partial membership of that object. Fuzzy c-mean clustering is widely used for medical image segmentation [20]. The segmentation results in large number of clusters. We apply vertical integral projection to separate every tooth on the maxilla and mandible as depicted in Fig. 7.

Data Augmentation

Deep convolutional neural network [21] shows better performance with large dataset. Data augmentation

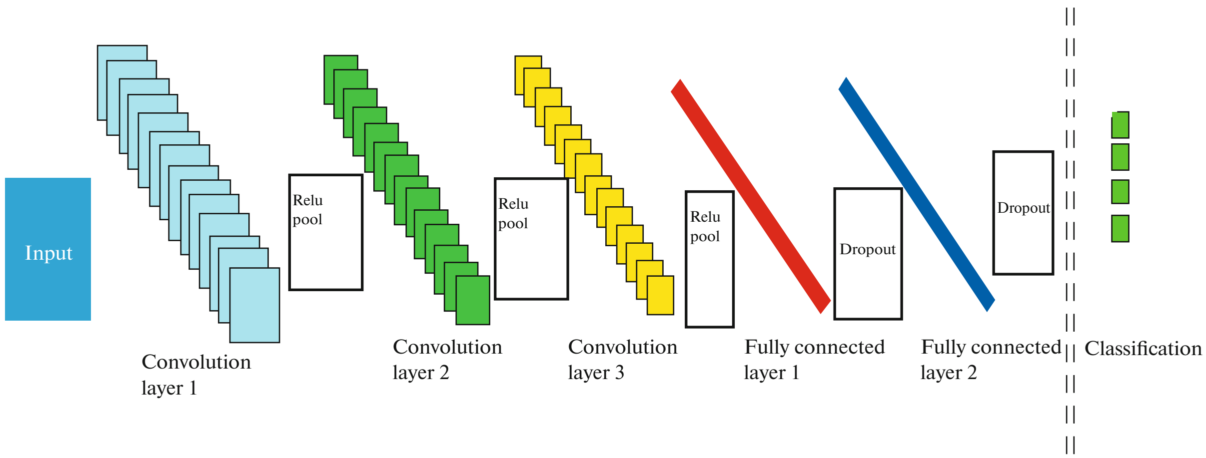

Fig. 4. Architecture of 6 layer deep convolution layer network for classification of dental panoramic images.

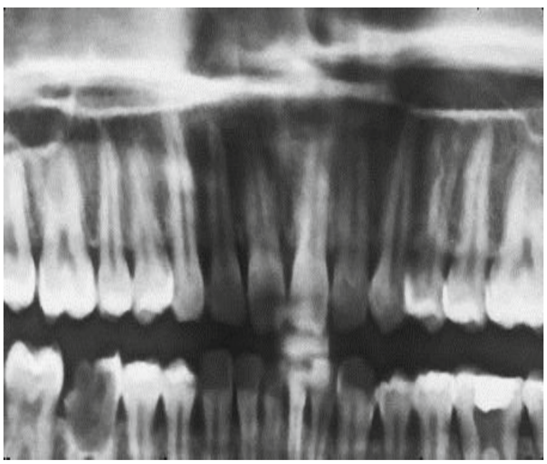

Fig. 5. Dental panoramic image after preprocessing.

Fig. 6. Fuzzy c means clustering.

is defined as the process of creating new dataset from the dataset we already have. Due to small amount of real time medical data available for training; it is very difficult to handle the deep convolutional neural network and the lesser amount of dataset leads to overfitting. Hence, to prevent overfitting, we augment the dataset by applying various data augmentation techniques. Literature survey shows that data augmentation has been applied by Perez and Wang [32] for image classification using deep learning. Lee et al. [33] have also used data augmentation techniques for detection and diagnosis of caries using deep convolution neural network. Rotation, translation and scaling [22–25] are some of the transformation methods to generate the new instances from the original instances available from the medical dataset. The augmented dataset has been generated by rotating the dental images with angle of 90°, 180°, and 270°. Data augmentation helps the 6-layer convolutional neural network to learn from the different patterns augmented to increase and boost the overall performance. Before data augmentation, the dataset consisted of 400 dental panoramic images resulting in approximately 12000 dental images of various tooth, and after rotating the dental images at various angles a total of 48000 dental images are generated for both training and testing of 6-layer deep convolution neural network. All the dental images of premolar, molar, canine and incisor were combined in order to avoid any bias of classification using 6-layer deep convolutional neural network. The result of dental images without and with data augmentation are shown in Table 1.

Teeth Numbering

The numbering of teeth implies assigning a particular number to each tooth based on the universal teeth numbering system [26]. Panoramic dental images are captured from either the left or the right of the jaws [26]. Each radiograph contains molar, premolar, canine and incisor in both the maxilla and mandible. So, the maximum number of teeth in each jaw will be 16 as depicted in Fig. 2. There are 6 molar, 4 premolar, 4 canine, and 8 incisors on the maxilla and mandible

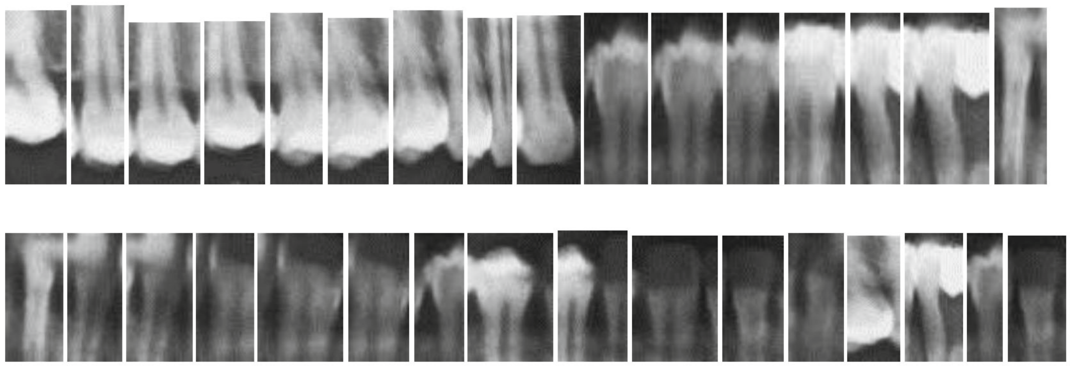

Fig. 7. Teeth of the panoramic dental images after vertical integral projection.

respectively. The universal numbering system [27] uses consecutive integer beginning with upper right third molar and count clockwise finishing at lower right third molar. Assuming that panoramic images are not rotated the molar is on the left in most of the radiographic images. The results of the numbering are fed as input to the 6-layer deep convolutional neural network.

Network Architecture for Classification

The 6-layer deep convolution neural architecture is composed of 3 convolution layers and 2 fully connected layers and 1 classification layer. The input to the 6-layer deep convolutional neural network consists of the features detected after numbering the dental tooth according to universal numbering system. The 3 convolution layers are connected by 3 rectified linear operator (Relu) layers and maxpooling layer [28]. The last classification layer has 4 neurons, which corresponds to the values of canine, incisor, molar and premolar respectively. Figure 4 describes the architecture of 6-layer deep convolutional neural network for classification of dental panoramic image. The size of the input image is $286 \times 286 \times 1$. The first convolution layer has 52 filters of size 7×7 pixels, stride of 2 pixels and no padding which is followed by Rectified linear unit and a max pooling layer of value 3×3 region and stride of 2 pixels. The output of convolution layer 1 is $52 \times 69 \times 69$ which is input to the second convolution layer. The convolution layer 2 has 256 filters of size 5×5 pixels, stride of 2 pixels and no padding which is followed by Rectified linear unit and a max pooling layer of value 3×3 region and stride of 2 pixels. The output of convolution layer 2 is of size $256 \times 15 \times 15$ pixels which is input to the third convolution layer. The convolution layer 3 has 156 filters of size 3×3 pixels, stride of 2 pixels and no padding followed by Rectified linear unit and max pooling layer of 3×3 region and stride of 2 pixels. The output from this layer is given to fourth layer, which is a fully connected layer with 512 neurons. This is followed by dropout layer with probability of 0.5. The fifth layer is another fully connected layer with 512 neurons. This is followed by dropout layer with probability of 0.5. The last layer is classification layer, which maps the input to 4 output classes.

EXPERIMENTAL RESULTS AND COMPARISONS

A 6-layer deep convolution neural network was used to classify each tooth into 4-tooth types namely incisor, canine, premolar and molar. This proposed smaller network design proves to be efficient as compared to the other larger architecture convolutional neural network applied in [21, 29]. 400 dental panoramic images were used for classification using 6-layer deep convolutional neural network. These 400 dental panoramic images were firstly segmented and then divided into training and testing dataset. Firstly, image processing was applied to dental panoramic images to remove the background and irrelevant data. The dataset is preprocessed in order to achieve enhanced and clear dental panoramic dental images. Figure 5 represents the result of dental panoramic images after applying median filtering. After preprocessing 400 dental panoramic images were segmented using fuzzy c-mean clustering and vertical integral projection. After segmentation, 12000 separate dental tooth images are obtained. The original dataset of 12000 dental images was divided into 7200 training images and 4800 testing images. After data augmentation, 48000 dental tooth images were

Table 1. Comparison of performance of original and augmented dataset for classification of dental images by 6-layer convolution neural network

Index	Original dataset	Augmented dataset
Sensitivity	90%	98%
Specificity	85%	92%
Accuracy	92%	95%

Table 2. Confusion matrix of classification result for original dataset

	Molar	Premolar	Incisors	Canine
Molar	2000 (97%)	40 (2%)	20 (1%)	0
Premolar	150 (10%)	1364 (86%)	20 (1%)	6 (0.3%)
Incisors	0	8 (1%)	662 (95%)	30 (4%)
Canine	0	30 (6%)	70 (14%)	400 (80%)

Table 3. Confusion matrix for classification result with augmented dataset

	Molar	Premolar	Incisors	Canine
Molar	7000 (99%)	15 (0.3%)	5 (0.8%)	0
Premolar	200 (3%)	6201 (96%)	5 (0.7%)	4 (0.6%)
Incisors	3 (0.6%)	190 (4%)	4207 (87%)	400 (9%)
Canine	0	10 (0.1%)	70 (7%)	870 (91%)

obtained which were divided into training and testing dataset. Sixty percent (28800) of the images were used for training and 40% (19200) were used for testing. Original dataset and the augmented dataset are also compared. Table 1 shows the performance of original and augmented database using 6-layer deep convolutional neural network for classification. The accuracy of the original dataset is 92% and the accuracy of the augmented dataset is 95%. Hence, the augmented dataset has better accuracy than the original dataset due to large amount of data. There is also the improvement in the specificity by 7% and the sensitivity by 8% in the augmented dataset as shown in the Table 1. Tables 2 and 3 represent the confusion matrix of the original dataset and augmented dataset classifying the tooth into molar, premolar, canine and incisor respectively. The misclassification is mainly found in the neighboring tooth (Fig. 8).

In order to confirm the functioning of 6-layer deep convolutional neural network for classification of tooth, receiver operator curves (ROC) between True positive rate (TPR) and false positive rate (FPR) were plotted. Figure 9 represent the ROC curve for augmented dataset using 6-layer deep convolutional neural network with an accuracy of 95%. Figure 10 shows the ROC curve of the original dataset using 6-layer deep convolutional neural network with an accuracy of 92%. The classifier is considered reliable since the area under the curve (AUC) is close to 1. The related terms are explained below.

True positive rate (TPR). The correctly classified data tuples form the true positive rate.

False positive rate (FPR). The incorrectly classified tuples are defined as the negative data tuple.

Accuracy. The ratio of correctly classified dataset and the negative classified dataset form the accuracy.

Our method outperforms the method proposed by Miki et al. [21], that was also based on the successful classification of dental panoramic images. They used Alex net architecture for classification and numbering of teeth of dental cone-beam computed tomography images. They worked on a different dataset of 52 dental CT images and achieved the accuracy of 88% without augmentation (for proposed method accuracy is 92%) and 91% with augmentation (for proposed method accuracy is 95%). The efficacy of our proposed system is compared with the method proposed by Miki et al. [21] by using the same 400 dental images dataset in Table 4. The results clearly prove that our proposed method is optimal. The proposed method also outperforms the method postulated by Kuo et al. [29]. They used CNN for classification of dental panoramic radiography images. The method preprocesses

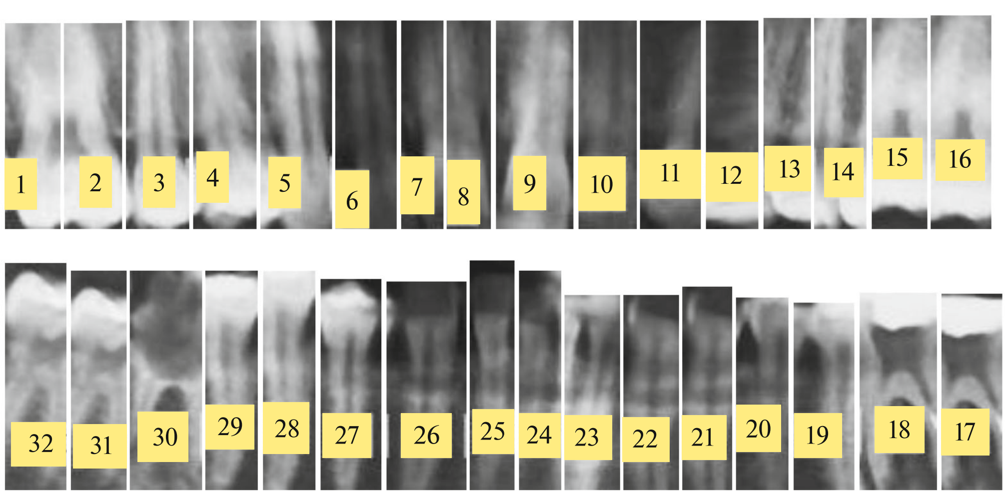

Fig. 8. Numbering of the dental panoramic images according to universal numbering system.

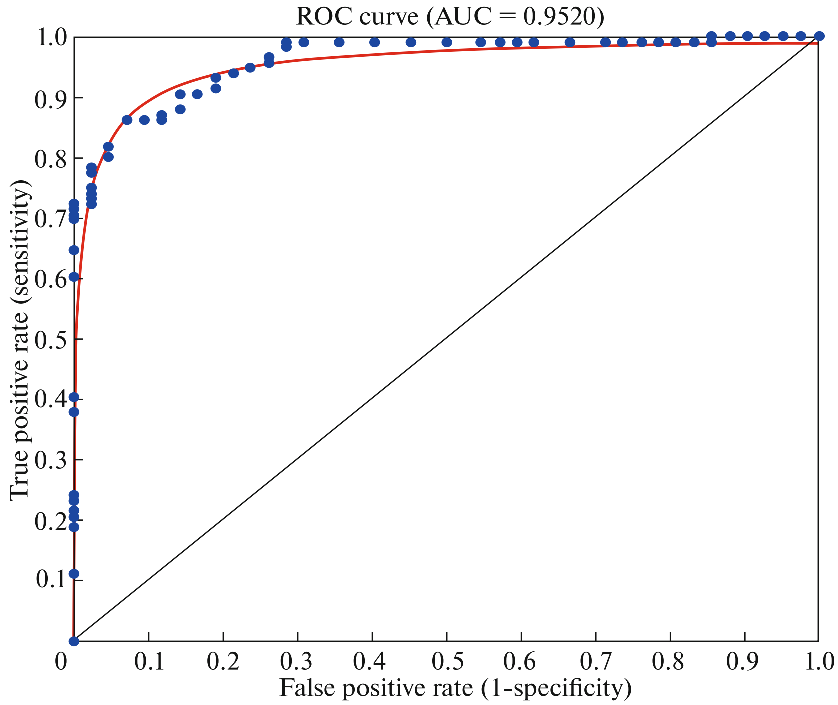

Fig. 9. (Color online) ROC curve of augmented dataset using 6-layer deep convolutional network.

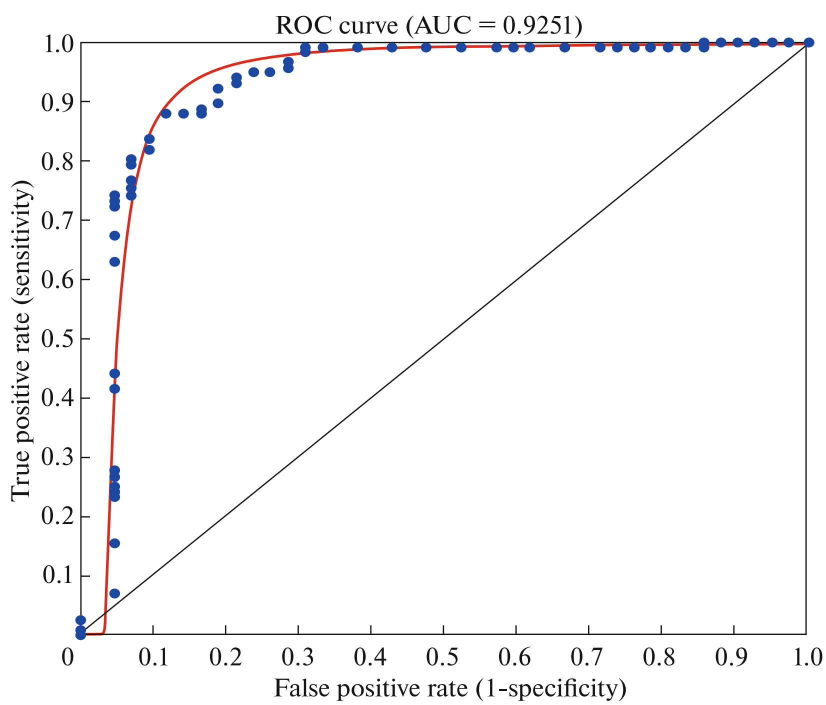

Fig. 10. (Color online) ROC curve for original dataset using 6-layer deep convolutional network.

and normalizes the images. Based on the images the final testing datasets are generated which helped in generating the results. The accuracy rate of the method was 85.3% with 250 dental panoramic dental radiographs.

CONCLUSIONS

This paper utilizes a 6-layers DCNN architecture for classification of dental panoramic images into molar, premolar, canine and incisor. Classification accuracy has been calculated with original dataset

Table 4. Comparison between 6-layer CNN and Alexnet architecture [21]

	6 layer convolutional neural network	Alexnet
Accuracy without data augmentation	92%	89%
Accuracy with data augmentation	95%	93%

(400 panoramic images segmented into 12000 tooth images) and augmented dataset (48000 segmented tooth images). The dental panoramic images were segmented using fuzzy c-mean clustering and vertical integral projection. Numbering of teeth was also applied to the dental images according to the universal numbering system. The high classification accuracy 92% of the original dataset and 95% of augmented dataset proves the efficiency of the proposed system.

COMPLIANCE WITH ETHICAL STANDARDS

The authors declare that they have no conflict of interest. This article does not contain any studies involving animals or human participants performed by any of the authors.

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