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Dental Biometrics Segmentation on Panoramic X-Ray Images using Computational Intelligence Approach

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***Abstract*—Dental Biometric is a new field of study in the sector of biometrics identification. This technique can be sometimes used instead of the usual fingerprint biometric identification. In most of the cases, Dental Biometric credentials come handy to analyze the details of a dead person where, the Dental Biometrics of the person before death and the person after their death could potentially explain various reasons for their death and could justify their identity after death. Neural Networks have the potential to learn about anything using their complex construction structure. Here, x-ray copies of the dental teeth structure of a potential individual are given or fed to the network and the neural network with the help of an object detection platform such as OpenCV2 detects the teeth structure and can visualize the teeth structure with x-ray of that individual alone. As the neural is now able to see the teeth, it can learn a lot of crucial details about it from the picture it can understand. The interpretation about the teeth contours and the number of teeth is made along the way. The proposed methodology has better accuracy than the fuzzy clustering relevant methods. Also Suggested to use the appropriate values of parameters that should be opted for the algorithm.**

***Index Terms*— Dental Biometric, UNet, OpenCV2, image processing.**

I. Introduction

As there is a greater availability of medical digital data, expanding processing power and advances in artificial intelligence, computer-aided diagnosis (CAD) has made tremendous progress during the previous two decades. CAD systems that aid radiologists, physicians in decision-making are used to solve a variety of medical issues, notably breast and colon cancer identification, lung disease classification, and brain lesion identification. Digital radiography's growing popularity encourages more research in the field. Radiographic image processing has now become a major issue of automation in dentistry, as radiographic information is a vital aspect of diagnosis of dental health monitoring, and treatment planning. Several investigations are done in the last decade to address the problem of teeth detection. There have been several suggested pixel-level techniques for tooth detection that were based on classic computer vision techniques like thresholding, histogram equalization etc. With enough recall (sensitivity) one can help the computer to be able to distinguish the teeth. On CT images too, various techniques have been utilized and a manual method to place coordinates surrounding each tooth has been developed.

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A. Teeth Analysis

There are basically two processes for tooth numbering: segmentation and classification. The width to height teeth ratio and crown size extract features from segmented teeth, whereas the wavelet Fourier descriptor is used to get the geometry of the teeth. The models like Support vector machines (SVMs), sequential based algorithms, and feedforward neural networks (NNs) are used to characterize teeth.

B. Convolutional Neural Networks (CNN)

CNNs are used in this study for the purpose of tooth detection and tooth numbering. CNNs are a common type of deep feedforward neural network design, and they're frequently used for image recognition. CNNs are most popular NN for the past two decades, but the real revolution in deep learning came after the design of AlexNet architecture. As this architecture significantly outperformed other teams in the ImageNet Visual Recognition Competition challenge. Since then, CNNs have seen rapid development. CNNs are currently used in a wide range of applications and represent a cutting-edge solution to various computer vision challenges.

II. DATASET

From January 2016 to March 2017, 1574, panoramic samples of radiographs is randomly selected from the X-ray's provided by Reutov Stomatological Clinic, Russia. The database doesn't not include any other features like gender, age, time etc. The tooth detection and identification models were trained in the training group, while the software's performance was verified in the testing group. The XG-3 - Sirona Orthophos X-ray machine was used to capture all panoramic radiographs (Sirona Dental Systems GmbH, Bensheim, Germany). Ground truth comments for the photographs were provided by five radiology professionals with varied levels of experience. Experts are instructed to draw bounding boxes around all teeth with high-resolution panoramic radiographs. Due to the skewness in the data collection, complete anonymzed data is used. The Steklov Institute of Mathematics in St. Petersburg, Russia, made a formal decision that the use of radiographic material for this work was exempt from ethics committee or IRB approval.

III. SYSTEM ANALYSIS

The technique demonstrated here uses panoramic radiographs as an input. To identify the borders of the teeth, the teeth detection module examines the radiograph. It is then cropped using the anticipated boundary boxes from the panoramic radiograph. The model classifies each cropped region using the FDI, then heuristics is used to produce the final teeth numbers. The system outputs the bounding box coordinates and matching teeth numbers for each detected tooth on the image. The diagram shows the entire architecture and workflow.

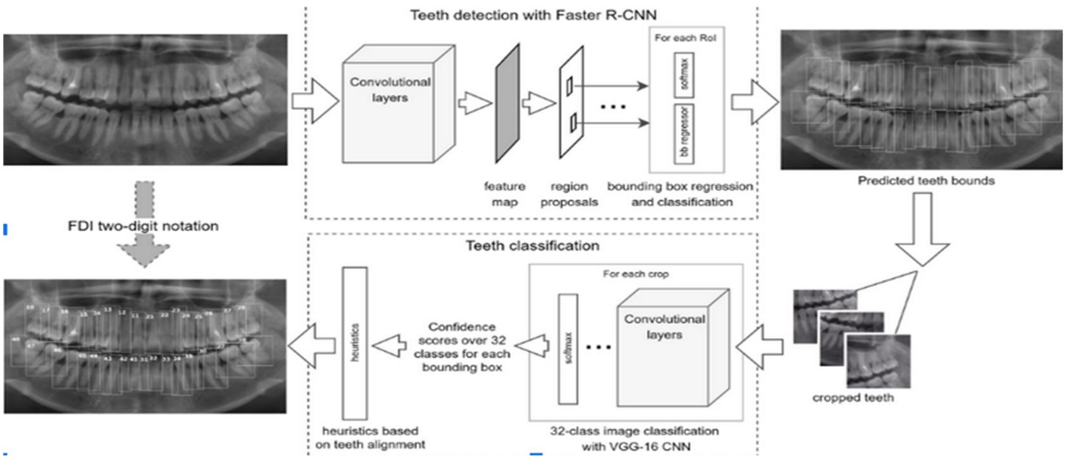

Figure.1: Process of Teeth Identification System

IV. MODELS

A. Deep Learning Models

The suggested approach makes use of deep learning techniques. Deep learning enables a computer programme to extract and learn attributes from the input data to understand previously unheard examples. Deep learning techniques stand out because they can learn directly from raw data input, such as the pixels in pictures, without the requirement for manual feature engineering. [1]One of the most popular deep learning techniques for image recognition is deep CNNs. To efficiently represent and learn hierarchical features at various levels of abstraction, CNN designs take advantage of unique properties of image input information, such as spatial relationships between objects; see LeCun et al. for a thorough description of deep learning techniques.

B. UNET Model Neural Network

The encoder and decoder were the two essential parts of the introduced technology. The covenant comprises various first in the encoder, followed by the pooling layers. It is used to extract the image's factors. To enable translation, the second portion decoder utilizes transposed convolution. It's an F.C joined layers network yet again.

C. Teeth Detection

The Faster R-CNN model is used in the teeth detecting method. 15 Faster R-CNN arose from the A fast R-CNN infrastructure that used the R-CNN methodology (Region-based CNN). It is challenging to find the areas of interest through object detection. R-CNN offered a unified strategy for both regions of interest proposal generation and object localization. Using Fast R-CNN, which streamlined the pipeline and optimized computation, improved R-performance for CNNs. Finally, a CNN-based method that was much more sophisticated was presented by Faster R-CNN.The R-CNN is made up of two parts: the object detector and the regional proposal network (RPN). RPN proposes region of interest i.e teeth in this case. The object detector makes use of these recommendations to better localize and categories the objects. Both modules produce feature maps, which are condensed versions of the source image, by using the CNN convolution layers that lie beneath. In contrast to standard computer vision algorithms, which demand hand-engineering of the features, the features are derived during the training phase.

By moving the window over the feature map and creating potential bounding boxes called "anchors" at each window point, RPN creates regional suggestions. The RPN employs the specific regressor to narrow the bounding box and determines the likelihood that each anchor will contain an object or a background. The top N-ranked region ideas are then sent to the object detection network.[2] The object detector generates the final bounding box coordinates for a two-class detection task after refining the class value of a region to determine whether it is a tooth or a background. Model weights that had been pre-trained on the ImageNet data set were used to create the fundamental CNN. All of CNN's layers were adjusted because the data set is sizable enough and differs enough from ImageNet. With exponential decay following, the learning rate was initially set at 0.001.

D. Teeth Numbering

The teeth are numbered by a convolutional architecture called VGG-16. The model was taught to estimate the number of teeth using the two-digit notation. This module categorizes the teeth using the output from the teeth detection module. Based on the anticipated boundary bounds, it crops the teeth. Each clipped image is then given a two-digit tooth number by the VGG-16 CNN. The classifier begins with a set of confidence ratings for each of the 32 classes, estimating the likelihood that each bounding box will contain one of the 32 potential tooth numbers. The classified data is again processed by custom heuristic algorithm to enhance prediction results. This process is carried out so that each portion of the tooth appear only once.

Like how they were used for teeth detection, the weights learned on ImageNet dataset is then used to initialize the CNN model. Based on annotations X-rays, cropped images were created for training. [4] The cropping process was modified to include nearby structures, which increased the CNN's prediction quality by providing context. To further increase the variety of the data set, the images were improved. 64 batches were used to train the CNN. The Keras library and TensorFlow serve as the backend for the dental numbering module, which is developed in Python.

V. Results and Discussion

In the figure:2, a single input x-ray image from a large amount of input x-ray images loaded into the program has been displayed. This image is not the raw version of the input but is the processed clear image of the input given to the program.

In the Figure:3, another image of the same input image displayed in the figure.1 is displayed but with a renewed sense of perceptiveness. Here, the input image is filled with yellow color and through this one can understand that the program using yolo successfully detects the teeth in the x-ray image loaded to the program.

<matplotlib.image.AxesImage at 0x7f9e38ef19a0>

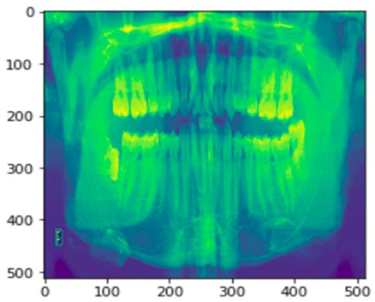

Figure.2: Clear Image of Input X-ray

<matplotlib.image.AxesImage at 0x7f9e37613220>

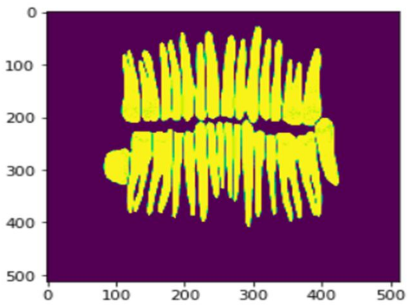

Figure.3: Another view of same image computer visionated

conv2d_14 (Conv2D)	(None, 256, 256, 64)	110656	concatenate_2[0][0]
dropout_7 (Dropout)	(None, 256, 256, 64)	0	conv2d_14[0][0]
conv2d_15 (Conv2D)	(None, 256, 256, 64)	36928	dropout_7[0][0]
batch_normalization_7 (BatchNor	(None, 256, 256, 64)	256	conv2d_15[0][0]
conv2d_transpose_3 (Conv2DTrans	(None, 512, 512, 64)	65600	batch_normalization_7[0][0]
concatenate_3 (Concatenate)	(None, 512, 512, 96)	0	conv2d_transpose_3[0][0] conv2d_1[0][0]
conv2d_16 (Conv2D)	(None, 512, 512, 32)	27680	concatenate_3[0][0]
dropout_8 (Dropout)	(None, 512, 512, 32)	0	conv2d_16[0][0]
conv2d_17 (Conv2D)	(None, 512, 512, 32)	9248	dropout_8[0][0]
conv2d_18 (Conv2D)	(None, 512, 512, 1)	33	conv2d_17[0][0]

Total params: 13,423,361
Trainable params: 13,420,481
Non-trainable params: 2,880

Figure.4: UNet model operations

The above figure.4 shows the operations of the UNet Model that was implemented by the program. The UNet model primarily makes sure that the image detected by the yolo program already is understood further. The images loaded to the model are expected in the dimensions (512,512) so that the model is implemented better.

0.955887187610973

Figure.5: F1_Score of the Model

In the figure.5, the f1 score of the UNet model implemented previously has been given. The score implies that the model is very good in the detection of the teeth x-ray images given to it. It can also be said that the model scored a 95% in the f1_score calculated for this model.

In the figure.6, the successfully predicted mask or the teeth of the test images by the model fitted has been displayed. The model in the program now understands or reads from the x-ray images provided containing the teeth images and the proof that it detects the teeth successfully is implied by this figure.[5].

In the figure.7, a contoured x-ray image of the test images given to the model has been displayed. Contours are used here as a change in the view of the x-ray image. Here, only the boundary of the teeth detected has been marked providing a new perceptive. Like the previous image, even this figure is evidence of a proof that the model can detect the teeth in the x-ray image.

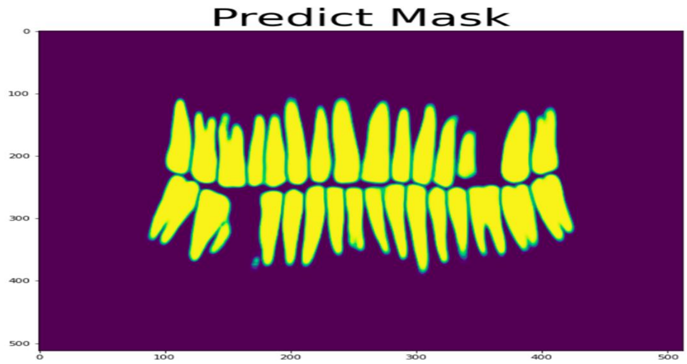

Figure.6: Successful predicted mask

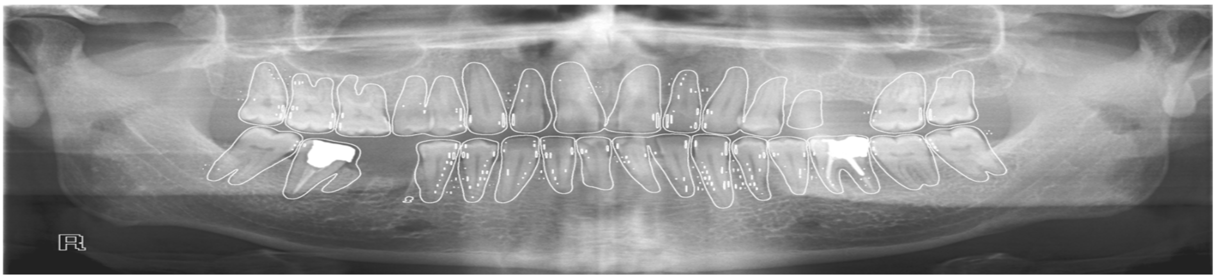

Figure.7: Contoured X-ray image

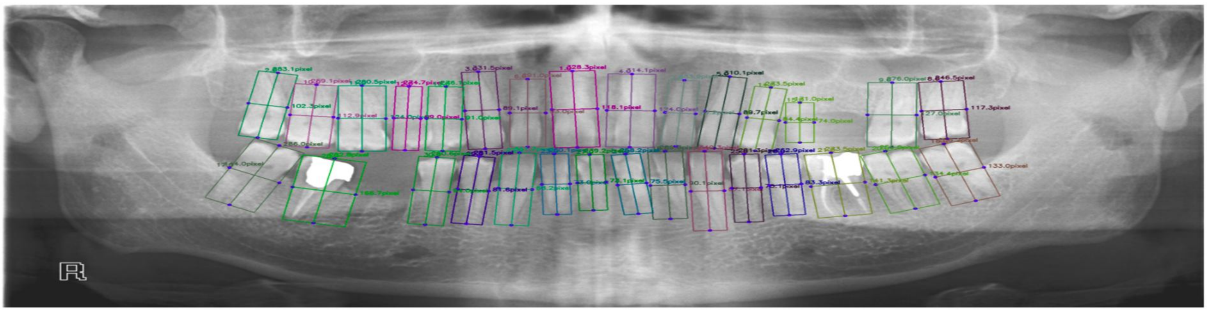

Figure.8: Detailed Detection of the teeth

In the figure.8, a detailed detection view of the teeth x-ray image given to the model as a test image is displayed. The pixel details of every tooth detected by the model has been displayed next to it. This can significantly help technicians as these details have been computed easily by the model now that it is detecting and understanding the x-ray image of the teeth given to it.

30 Teeth Count

Figure.9: Total teeth detected

In this figure, the total teeth that have been detected by the model so far in that image given to it as a test x-ray image has been given. Note that usually people can have about 28 to about 32 teeth in case of when some or all wisdom teeth have sprouted in that individual. In some cases, people may have less teeth as it would have fallen out. All these cases make it more important to know the number of the teeth in a person through the x-ray image provided.

VI. Conclusion

The Dental Biometric System's UNET model-based design is particularly effective at identifying the biometrics of the teeth. Panoramic radiographs can be a very effective tool to support patients' diagnosis and to define a treatment plan to them. The use of segmentation models to detect teeth and their exact limits can be of paramount importance for eliminating a task that is quite susceptible to human failure. Biometric traits can be used for authentication and personal security. [3,6]It is possible to collect even the pixel details and measurements of the teeth shown in the panoramic x-ray photographs. These findings are extremely helpful for forensic and dental research. Based on the F1-score, this model provides 95% accuracy. By ensuring that the UNET model effectively detects additional information about the teeth, such as their type and any surgical identification in them, this study can be further refined. The work's results are acceptable and offer directions for a more superior and efficient dental segmentation procedure. The results obtained in this work are satisfactory and present paths for a better and more effective dental segmentation process.

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