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Detection of Gingiva Phenotype using Deep Learning

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***Abstract*: In the field of computer science, technologies are evolving in a very rapid phase in order to solve real world problems in more efficient ways. There is huge scope in the field of medical science to solve a problem by leveraging computer science techniques and principles. Similarly, here also we tried to solve one of the problems of the dentistry field by using the state-of-the-art technologies like Artificial Intelligence and Machine Learning. Orthodontic problems are very painful and it indirectly causes various diseases. Gingiva related issues also fall in the orthodontics category and are sometimes ignored until it's too late to recover from it. The treatment of this issue is very painful and sometimes costly. Identification of gingiva is the very first step for the treatment of any Dental disease and traditional methodologies used to measure the gingival tissue are very painful and costly. To overcome this problem, we have developed an advanced algorithm which harnesses the power of Deep Convolutional Neural Network and Transfer learning to solve this issue. We synthesized the set of ROI extracted intraoral images and then fed all the images to deep CNN. Here we tried to provide an end-2-end solution to the medical practitioners in order to identify gingival phenotype from just a snap of an image. In this way by leveraging the computer science-based technologies we made this process painless and less costly.**

***Keywords*: Deep Learning, Convolutional Neural Network, Gingiva phenotype, Image processing.**

1. Introduction

The tissue of the upper and lower jaws that surrounds the base of the teeth is called the gingiva. Measuring the thickness of gingiva in the faciopalatal dimension and classifying it as thick or thin is called phenotype of gingiva. When the faciopalatal thickness of gingiva is greater than 1.5mm we classify it as thick phenotype and when it is less than when 1.5mm we classify it as thin phenotype. Before starting any dental treatment procedure, it is important to for a clinician to know the phenotype of gingiva. Gingiva with a thin phenotype causes gum recession. In gum recession gaps or pockets are formed between the teeth and the gingiva. This makes it easy for the disease-causing bacteria to build up inside these gaps and if left untreated it will damage the supporting structure of teeth which will ultimately result in tooth loss. There are several ways of determining the thickness of gingiva such as:

Direct Method: Direct method is slightly painful for patients, in direct method doctor uses anesthesia and then the endodontic probe is used to pierce the gingiva. A rubber stopper is used to mark the thickness and a digital caliper is used to take an accurate measurement, if measured thickness was greater than1.5 mm, it was categorized as a thick phenotype. When the thickness was less than 1.5 mm, it was considered a thin tissue phenotype. This method has inherent limitations, such as precision of the probe, which is to the nearest 0.5 mm, the angulation of the probe during probing and distortion of tissue during probing.

Fig. 1. Direct method

Visual Examination: Visual assessment is a technique which is frequently used to determine the gingival biotype. In this technique, no tools are necessary and it is quite simple and straightforward since each biotype exhibits its typical features. In this method, gingival biotype is clinically evaluated on the basis of general appearance of gingiva around teeth. The gingival biotype was considered as thick if the gingiva was dense and fibrotic and thin if the gingiva was delicate, friable, and almost translucent. The advantage of this method is that it is non-invasive. However, it has been found that it has low accuracy and high intra examiner variability.

Probe Transparency: Periodontal probe is placed in the sulcus of the midfacial aspect of tooth and gingival biotype is categorized on the basis of the visibility of underlying periodontal probe through gingival tissue. It is considered as thick if not visible and thin if visible.

In this project we have developed a web- based application “Gingiva Phenotype”. This application takes image as an input. State of the art deep learning algorithm, CNN (Convolution neural network) is used to process these images and classify the

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image as thick phenotype or thin phenotype.

Fig. 2. Probe transparency

2. Literature Review

Dima M. Alalharith et al., (2020) in this paper, the author tries to detect and diagnose the problem related to periodontal diseases. The dataset contains 134 images which are further divided into training and testing dataset in 80:20 respectively. Two models were developed, one is for detection of ROI and another is to process the extracted part. Various types of CNN based algorithms used. We considered this paper as a base for our project in order to develop a more optimized model based on these findings here we tried to optimize the time complexity and prediction accuracy of the model so that it handle chunk of user inputs

Adileh Shirmohammadi, et al, (2008) in this study was designed to determine the atomic features of gingival in a group of 100 subjects. The age of all subjects are in between 20-24 with no prior periodontal or orthodontic treatment history until the publication of this paper. In this study all the subjects are undergone for the procedure of measuring Gingiva. The measurement of Gingiva is identified with the help of probe transparency method (Although there are few more traditional methods used to measure gingiva), In this study they determine the anatomical features of the gingiva which are very important in appropriate periodontal treatment planning.

From this paper we concluded that the probe transparency method is one of the only solutions in order to identify gingiva and this method is also painful. Concluding point here is there could be a more robust way to address this painful problem into a painless problem using Computer science based technologies.

Raja'a M, et al, (2016) Computer Science based technologies plays an important role in many domains to solve real world problems. Technologies like Virtual Reality and Augmented Reality are mentioned here showcasing how these technologies are leveraged by professionals to develop sophisticated problem-solving mechanisms. Virtual reality and augmented reality provide immersive simulation in medical practices. Other than that, practices like CAD/CAM also used to design complex simulation environment and realistic modelling. The concluding part from here is to solve a problem using optimal approach, existed solutions are just to address the problem but it can further evolve to address the same problem in more efficient way.

R. G. Shiva Manjunath, et al, (2015) In this study 336 patients was evaluated to check the thickness of Gingiva, Both male and female subjects are included in order to identify generalize output, Probe transparency method is used here to identify the thickness of gingiva, The probe transparency method is one of the painful method to identify the gingiva, In the result the significant difference were found in both male and female subjects, The key difference is 76.9% of males showed thick biotype compared to 13.3 % of females. Hence, we concluded from here that the orthodontic problems are more in females.

Joachim Krois, et Al, (2014) In this paper Joachim Krois and team explains about the methodology they used to treat the periodontist problem which is very closely related to our subject orthodontist. In this project they used a set of 2001 panoramic radiographs images they fed all this image data in deep feed-forward CNN (Convolutional Neural Network) from this technique they reduced the effort of dentists' diagnostic efforts when using radiographs. We conclude that a deep CNN would be the best fit to analyze the ROI of the image.

Anita Thakur , et al, (2016) in this study they tried to address risk factor-based diagnosis of Gum diseases using neural networks. According to them a feed forward neural network with back propagation was used for prediction of gum disease.

3. Methodology

A. Image Dataset Gathering

Images of the teeth are required for this project which were collected by Dr. Surekha Rathod at VSPM's Dental College and Research Center, Nagpur. The intraoral images were collected by the doctor with the help of a camera and cropped to concentrate on gingiva of four teeth i.e., teeth number 12,11,21,22. The sample image is shown below.

Fig. 3. Sample image

After collecting an intraoral image, the doctor used anesthesia on the patient. The endodontic probe was used to pierce the gingiva and a rubber stopper is used to mark the thickness. A digital caliper is used to take an accurate measurement. When the process of measuring the thickness of gingiva of these four teeth is done an excel sheet was created and the four values were written down. The average of these four values were calculated and if the calculated average was greater than 1.5mm the image was classified as thick phenotype and if it is less than 1.5mm it was classified as thin phenotype. Sample portion of the excel sheet is shown below,

	A	B	C	D	E	F	G	H	I
1	2	1.3	1.4	1.9	1.8		1.575		Thick
2	3	0.4	1	1	1		0.85		Thin
3	5	1.2	2	1	1		1.3		Thin
4	6	1.8	1.6	107	1.8		1.725		Thick
5	9	1.5	1.5	1.6	1.5		1.525		Thick
6	10	1.8	1.6	1.8	1.7		1.725		Thick
7	12	2	1.2	1	1		1.3		Thin
8	13	1.5	1.5	1.6	1.4		1.5		Thick
9	14	1.6	1.5	1.6	1		1.425		Thin
10	15	1.3	1.2	1.3	1.4		1.3		Thin
11	16	1.5	1.5	1.6	1.4		1.5		Thin
12	17	1.3	1.3	1.5	1.6		1.425		Thick
13	18	1.3	1.4	1.5	1.5		1.425		Thin
14	19	1.5	1.5	1.6	1.5		1.525		Thick
15	20	1.8	1.6	1.8	1.7		1.725		Thick
16	21	2	1.2	1	1		1.3		Thin
17	22	1.3	1.2	1.3	1.4		1.3		Thin
18	23	1.6	1.5	1.6	1		1.425		Thin
19	24	1	1	1.3	1.6		1.225		Thin
20	26	1	1.2	1.2	1		1.1		Thin
21	27	1.5	1.5	1.6	1.4		1.5		Thick
22	28	1	1	1	1		1		Thin
23	29	0.4	1	1	1		0.85		Thin
24	30	1.2	1	1	1		1.05		Thin
25	31	1.1	1.3	1	1.2		1.15		Thick
26	32	1.5	1.2	1.2	1.5		1.35		Thin
27	33	1.3	1.2	1.2	1		1.175		Thick
28	34	0.4	1	1	1		0.85		Thick

After gathering an image dataset from the doctor the images contained teeth which were not required. So, we created our teeth removing algorithm which helped us in obtaining the Region of Interest (ROI).

The algorithm first converts the RGB image into a grayscale image by using a function called RGB2Gray. This will return us a grayscale image for further processes.

After converting it to a grayscale image we made another function called ImageGenerator, which returns the RGB image without the teeth region i.e., Region of Interest (ROI). In this function we give two images as parameters (Original RGB image and converted to grayscale image). We compare each pixel value of grayscale image with the threshold value i.e., 175 in our model. If the pixel value of grayscale image is greater than threshold value then we make that pixel value 0 of grayscale image. With this we get the grayscale image in which teeth have been extracted/removed.

Now as our final step in obtaining the Region of Interest (ROI), we made another function called ValueChanger. This function takes both the original RGB image and Grayscale image after passing it through the ImageGenerator function which removes teeth from the image. Then it compares both the images and wherever there is a 0 pixel value in grayscale image it changes the corresponding value of that pixel in RGB image to 0, in all three channels.

After passing our image through all the three functions RGB2Gray, ImageGenerator and ValueChanger, we get the original RGB image without teeth which is our Region of Interest (ROI) and then we pass it to our model for further processing.

We used VGG16 pre-trained model for processing the images. The model was originally trained to predict thousand different classes, so we changed the last layer to predict only two classes with sigmoid as an activation function in the last layer. The model was compiled using Adam as an optimizer and binary cross entropy was used to calculate the loss.

4. Conclusion

We concluded that our research on identification of gingiva phenotype using deep learning, with extraction of region of interest using custom algorithm is very helpful in the field of medical sector especially in dentistry field. Earlier methods for identification of gingiva phenotype is invasive and painful for patient. Our implemented model is capable enough to classify phenotype using the images of patients.

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