A Web-based Patient Management System in Teeth Segmentation Using Deep Learning

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Abstract. Several advanced deep-learning methods have recently enabled the automatic segmentation of 3D dental models. However, the considerable computational cost of these methods usually results in time-consuming training and segmentation periods on edge devices, prohibiting effective preoperative planning. Thus, the aim of this paper is to propose a web-based patient management system in teeth segmentation using deep learning. The proposed deep learning method places significant emphasis on the coordinates of cell vertices, normal vectors, relative positions, and curvatures to enable precise and comprehensive teeth segmentation. Furthermore, an online platform can be employed for telemedicine, collaborative treatment and follow-up care in various regions or countries, thereby contributing to intelligent healthcare. The experimental findings of this study confirm that the proposed system significantly outperforms state-of-the-art techniques for 3D teeth segmentation and telemedicine.

1   INTRODUCTION

The World Health Organization (WHO) considers malocclusion to be one of the most significant oral health issues after caries and periodontal disease. Its prevalence varies greatly and is estimated to be between 39% and 93% among children and adolescents [1]. It is clear that malocclusion is not only a common issue, but it is also rapidly getting worse in adolescents. Computer-aided design (CAD) is widely adopted by orthodontists for preoperative planning and postoperative evaluation in the clinical practice of dentistry. Additionally, an ideal treatment depends significantly on a complete and accurate tooth model. However, it is really challenging for the segmentation of the teeth with morphological diversity from optical scanned models due to a large number of manual boundary selections [2-5]. Therefore, teeth segmentation is a time-consuming task primarily on the user's experience. Moreover, the use of CAD in medical applications requires highly specialized software and hardware. Multiple collaborators, remote collaboration, and interaction between them

both synchronously and asynchronously are consequently challenging. Hence, computer-supported collaborative work (CSCW) was proposed as a solution to overcome above issues by Greif and Cashman [6]. With the advancement of Internet technologies, the web-based system plays an important role in CSCW, particularly in the era of COVID-19. It enables users to share knowledge, collaborate on treatment planning, and communicate in a secure environment. Furthermore, users are not frustrated by incompatibilities between different systems or by the inability of applications to support multiple users in different settings. As a consequence, the creation of a cloud system based on deep learning is urgently required in order to improve the accuracy and efficiency of teeth segmentation, reduce the workload of users in practice, and achieve collaborative work.

2   RELATIVE WORK

Some efforts have been devoted to the development of teeth segmentation, which can be roughly categorized into projection-based [7-8] and geometry-based methods [9-11]. In practice, these techniques are typically semi-automatic and rely on user experience. Furthermore, it is sensitive to variations in tooth morphology for their performance. Some deep learning techniques have recently been proposed to enhance the traditional geometry-based methods. For instance, an end-to-end deep network [12-13] is proposed to learn hierarchically multi-scale contextual features and holistic features of the 3D dental surface for labeling. Cui et al. [14] propose a two-stage algorithm for tooth segmentation; all teeth are detected in the first stage, and each tooth is separated in the second stage. A two-stream graph convolutional network (TSGCN) [15] is proposed to learn discriminative geometric features from heterogeneous multi-view inputs for end-to-end tooth segmentation. To train a deep network for the above works, however, curvature information is lacking. Hence, the proposed method integrates the curvature information to enhance the previous works.

3   FINE-GRAINED LOCAL GEOMETRIC CONTEXT-BASED DEEP LEARNING

An overview of the proposed system is illustrated in Figure 1. The first step is to collect a studied dataset from a desktop scanner or intra-oral scanner from the Department of Dentistry at Kaohsiung Medical University. Data preprocessing, which includes mesh simplification, annotation, and augmentation, is the second step. The third step is to calculate an 18-D input vector describing each cell on the dental surface. The 18-D input vector includes the coordinates of cell vertices (9 elements), the normal vector (3 elements), the relative position (3 elements), and the curvatures (3 elements). The 18-D input vector is then to be the input of the deep learning. In the end, the teeth segmentation can be obtained and rendered in the proposed web-based system, as shown in Figure 1. More details are described in the following sections.
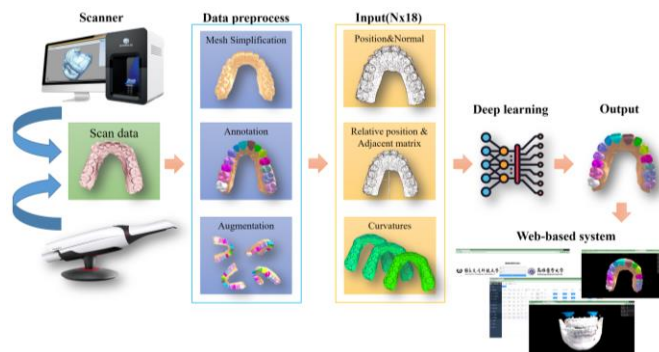

Figure 1: Overall flowchart of the proposed framework.

3.1 Data Preprocessing

The studied dataset consists of 85 scanned datasets. Each raw dataset contains approximately over 100,000 mesh cells. Thus, all datasets were simplified to 8,000 mesh cells while preserving the original topology because of insufficient graphic processing unit (GPU) memory during the training. After model simplification, all datasets were manually annotated to establish the ground truth. These annotated datasets were confirmed by dentists with more than ten years of experience in digital dentistry. Furthermore, we also augment the training dataset with random translation between -20 and 20, random rescaling between 0.7 and 1.3, and random rotation along the x and y axis between $-\frac{\pi}{4}$ and $\frac{\pi}{4}$, and along z axis between $-\pi$ and π. After the mesh simplification, annotation, and augmentation, some known information, including the coordinates of cell vertices, the normal vector, and the relative position, was collected as a 15-D input vector. On the other hand, the curvatures, including maximum curvature, mean curvature, and Gaussian curvature, were calculated as a 3-D input vector, as shown in Figure 2.
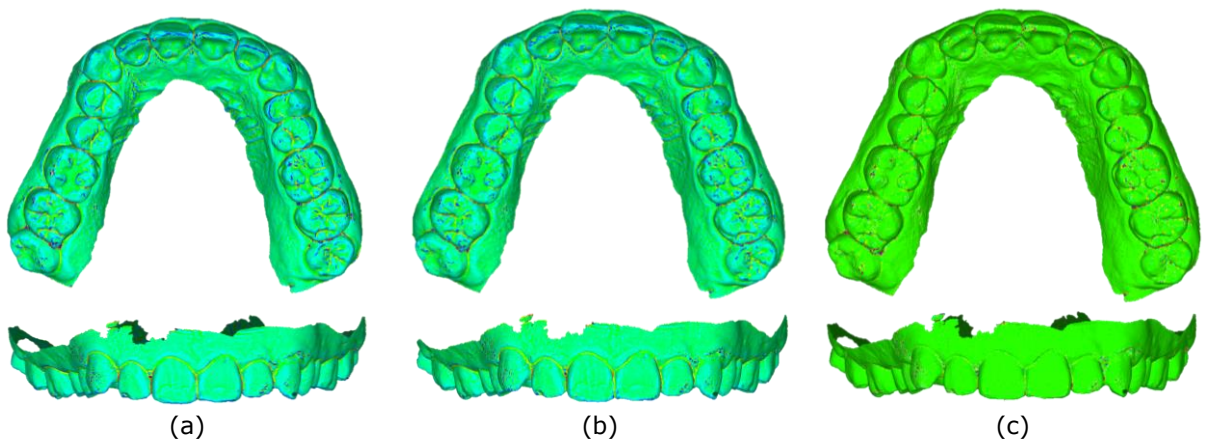

(a)	(b)	(c)

Figure 2: Curvature calculation: (a) Maximum curvature, (b) Mean curvature, and (c) Gaussian curvature.

After data collection, the proposed network input is an N x 18 matrix (e.g., N=8,000). Besides, the entire datasets were divided into two parts: 40 datasets for training and 16 datasets for validation were selected, respectively.

3.2 Deep Learning

In this paper, the proposed network is an extension of MeshSegNet. Firstly, the coordinates of three adjacent cell vertices, the normal curvatures, and the relative positions of cells respective to the whole surface are adopted as the primary network input. Secondly, multi-scale graph-constrained learning modules are used to hierarchically model multi-scale local geometric contexts on surfaces. Thirdly, a dense fusion strategy is done for dense skip connections combing local-to-global features. Finally, crown segmentation is predicted as an end-to-end prediction. The flowchart of the proposed deep-learning network is shown in Figure 3.

The raw input surface is an $N \times 18$ matrix $\mathbf{F}^0$, where N denotes the number of mesh cells. After the deep learning procedure, $\mathbf{P}$ is obtained as an $N \times (C + 1)$ matrix with each row denoting the probabilities of the respective cell belonging to different classes. The multi-layer perceptrons (MLPs) is adopted to extract increasingly higher-level geometric features for each mesh cell. In this paper, MLP-1 includes two 1D Convs with 64 channels. For MLP-2, three 1D Convs with 64, 128, and 512 channels are set, respectively. MLP-3 has four 1D Convs with 256, 256, 128, and 128 channels,

respectively. Besides, a feature-transformer module (FTM) is used to predict a transformation matrix and align the initial features for different cells onto a canonical feature space. Hence, it could improve the learning performance in subsequent layers [16].
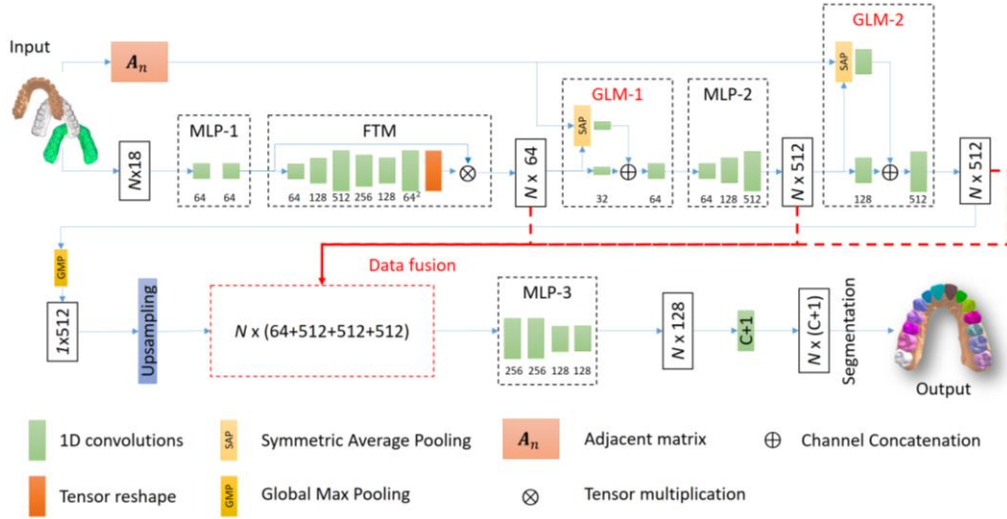

Figure 3: Proposed deep learning network.

Inspired by [13], two graph-constrained learning modules (GLMs) are employed to explicitly model the local geometric context on the input surface data. To construct GLM-1 and GLM-2, each cell is regarded as the centroid that defines a 3D ball with a specific radius. The cells within the respective ball are selected as the neighbors for each centroid. A $N \times N$ adjacent matrix is then constructed for the input mesh data. The radius in this paper is set 0.15 empirically. In comparison to MeshSegNet, the proposed network eliminates the additional 3D ball to reduce the calculation time. Based on A_N, GLM-1 first applies the symmetric average pooling (SAP), a graph-based fusion operation, to propagate the local contextual information onto each centroid cell. Assume $\tilde{A}_N = A_N + I$ is the adjacency with self-loops and $\tilde{D}_S^{-\frac{1}{2}}\tilde{A}_N\tilde{D}_S^{-\frac{1}{2}}$ is the corresponding symmetric-normalized adjacency, where $\tilde{D}_S$ denotes the diagonal degree matrix. The SAP operation in terms of $\hat{F}^1$ given A_N is defined as

$$\begin{cases} \tilde{F}^n = (\tilde{D}_S^{-\frac{1}{2}}\tilde{A}_N\tilde{D}_S^{-\frac{1}{2}})\hat{F}^n \\ n = 1,2 \end{cases} \tag{1}$$

where $\tilde{F}^1$ is the updated cell-wise feature matrix encoding local geometric contexts. After SAP, $\tilde{F}^1$ and $\hat{F}^1$ are further squeezed by the 1D Convs with 32 channels. Another 1D Conv with 64 channels is then used for fusion with the resulting feature matrices. On the other hand, a larger receptive field is adopted to learn multi-scale contextual features in GLM-2. Hence, the MLP-2 output is a $N \times 512$ matrix $\hat{F}^2$ and a $\tilde{F}^2$ is obtained from the second SAP operation. Both $\hat{F}^2$ and $\tilde{F}^2$ are then squeezed by the 1D Convs with 128 channels, which are finally concatenated across channels and fused by another 1D Conv with 512 channels.

A global max pooling (GMP) is applied to the GLM-2 output for generating the translation-invariant holistic features. These features encode the semantic information of the whole input surface. Furthermore, the local-to-global features from FTM, GLM-1, GLM-2, and upsampling GMP are concatenated densely. Then, a MLP-3 is used to generate a $N \times 128$ feature matrix. Finally, a $N \times (C + 1)$ probability matrix **P** is predicted by the MLP-3 output and a 1D Conv layer with softmax

activation. The batch normalization (BN) and ReLU activation are adopted in all 1D Convs of these MLPs and GLMs.

4 A WEB-BASED SYSTEM

In this paper, a web-based system is developed for the telemedicine, collaborative treatment, and follow-up in different regions or countries. Django serves as the backend, Vue.js and three.js serve as the frontend, and MySQL serves as the database. All models could be uploaded and visualized in the system.

4.1 A service-oriented Architecture in Cloud Computing

In this paper, a service-oriented architecture in cloud computing is based on Amazon Web Service(AWS). The architecture includes Route53, Web Elastic Compute Cloud, App Elastic Compute Cloud, ElastiCache and Relational Database Service, as shown in Figure 4.
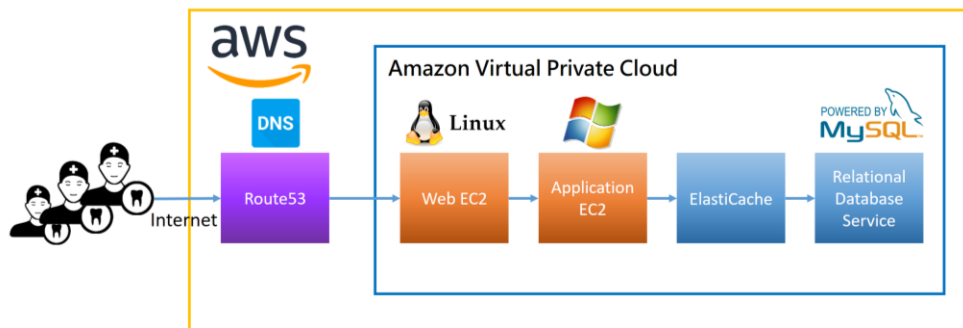

Figure 4: A service-oriented architecture in cloud computing.

In this research, Route53 is used to obtain a new domain name related hospital and manage a private Domain Name System(DNS) with Amazon Virtual Private Cloud(VPC). The VPC is a virtual network to create a private network for resources such as database and application server. In VPC, a web Elastic Compute Cloud(EC2) in Linux environment is created to control both inbound and outbound traffic. On the other hand, an application EC2 in a Windows environment is used to calculate the teeth segmentation via a pre-trained model, visualize 3D models, and perform effective database searching. Besides, an In-memory key value associated with one ElastiCache is adopted to improve the efficiency between the application and database. Finally, a Relational Database Service(RDS) is used to encrypt our databases using keys. In the RDS encryption, patient's data stored at rest in the underlying storage is encrypted for automated backups, read replicas, and snapshots.

5 EXPERIMENTAL RESULTS AND DISCUSSION

All experiments are performed on an Intel i7 processor with 16 GB of RAM and an 8 GB GeForce RTX 3060Ti GPU. The proposed deep network was implemented on Windows 11 with Python 3.7.6 and PyTorch 1.6.0+cu101. It is trained by minimizing the generalized Dice loss with the AMSGrad variant of the Adam optimizer (learning rate: 0.001; mini-batch size:10; number of epochs: 200).

5.1 Accuracy

In this paper, we compare the proposed technique with MeshSegNet[13] using the same experimental setup, loss function, and optimizer. A 3-fold cross-validation on the studied dataset is carried out to evaluate the segmentation performance. Based on the ground-truth annotations, the

outcomes of the crown segmentation are evaluated by Dice similarity coefficient (DSC), sensitivity (SEN) and training loss. The DSC shows the similarity between the predicted results and ground-truth. Besides, the SEN expresses the probability that the prediction is positive based on all positives in ground-truth. The DSC and SEN metrics are defined as

$$DSC = \frac{2 \times number\ of\ true\ positives}{number\ of\ true\ positives + number\ of\ false\ positives + number\ of\ false\ negatives} \tag{2}$$

$$SEN = \frac{number\ of\ true\ positives}{number\ of\ true\ positives + number\ of\ false\ negatives} \tag{3}$$

The plots in Figure 5(a) and (b) show that the training loss and validation loss decrease to a point of stability. Moreover, the segmentation performance is positively correlated with the DSC and SEN metrics, as depicted in Figure 5(c) and (d). Compared to [13], the proposed network exhibits faster training and validation times in terms of DSC and SEN convergences. Specifically, in the proposed network, the DSC and SEN for validation at the 28th epoch decrease from 0.74 to 0.59 and 0.75 to 0.6, respectively. On the other hand, in [13], the DSC and SEN for validation at the 28th epoch increase from 0.64 to 0.68 and 0.67 to 0.72, respectively. Notably, at the 200th epoch, the proposed network achieves the DSC and SEN of 0.93 and 0.93, respectively, for validation. In contrast, [13] achieves the DSC and SEN of 0.86 and 0.88, respectively, at 200th epoch for validation. Therefore, the proposed network demonstrates a significant improvement in performance, leading to fast convergence.
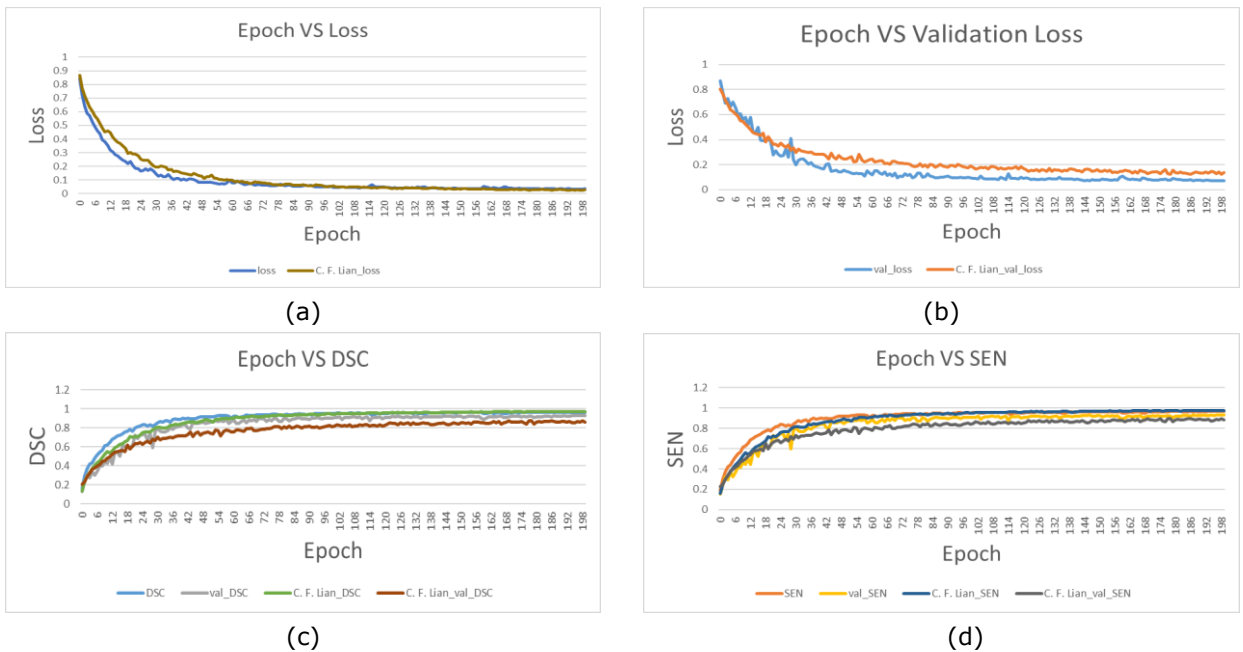

(a)

(b)

(c)

(d)

Figure 5: The training and validation loss of the proposed method: (a) Training loss, (b) Validation loss, (c) DSC, and (d) SEN.

Finally, the crown segmentation from the optical scanned models could be obtained by the training model and visualized on the proposed web-based system, as shown in Figure 6. As you can see,

the colorful labeling in different tooth positions means that the network could identify the specific tooth in different positions.
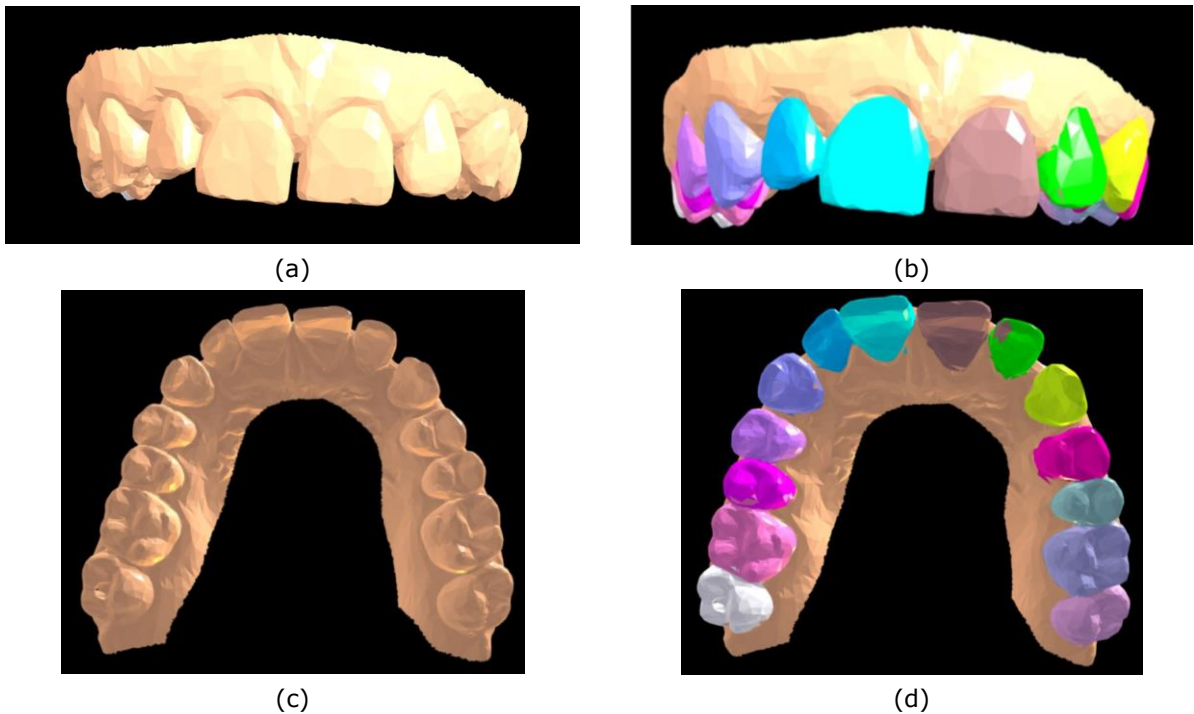

Figure 6: Visualization of representative segmentation results: (a) Front view, (b) Front view with segmentation, (c) Top view, and (d) Top view with segmentation.

It can be found that some mis-segmentation occurs on the occlusal surface and boundaries, as shown in Figure 7. The mis-segmentation could be improved via a specific graphic-cut post processing. Furthermore, combining multi-scale modules could increase the complementary information and improve the segmentation results.

Figure 7: Mis-segmentation: (a) Noises, and (b) Mislabeling.

5.2 A Web-based Patient Management System

In this research, three different roles, including dentists, clinics and laboratories, have the capability to log into this system, as depicted in Figure 8(a). After the logging in, they are required

to create a patient order and subsequently upload the patient's scan data via the system's frontend, as described in Figure 8(b). The system supports the STL, OBJ and PLY formats for scan data. The most important information during the patient order creation process is the type of scan data (mandible or maxilla). The backend of this system utilizes two separate pre-trained models for segmentation- one for the mandible and the other for the maxilla. The processing time for this segmentation is approximately 10 seconds. Finally, the system has the ability to render an online visualization and the segmentation could be downloaded, as shown in Figure 8(c).

| (a) | (b) | (c) |

Figure 8: A Web-based Patient Management System: (a) Log in, (b) Order creating and scan data uploading, and (c) Online visualization with segmentation result.

6   CONCLUSIONS

This paper aims to build a deep learning network for automatically segmenting crowns and to visualize the results on a web-based system. The proposed system can efficiently assist dentists in creating a complete and accurate teeth model for preoperative planning and postoperative evaluation. In conclusion, the advantages of the proposed system presented in this paper are as follows:

- Due to a large number of manual boundary selections required by the conventional approach of crown segmentation, it takes a lot of time. In the proposed system, a new structure of deep learning network is designed for automatic crown segmentation. Dentists only need to make minor adjustments for annotation refinement.
- Gaussian, maximum, and minimum curvatures are critical characteristics at every point on the surface. Thereby, the features are added to the proposed network to significantly boost performance.
- A web-based system is developed to have multiple collaborators, remote collaboration, and interaction with each other synchronously and asynchronously.

In our future work, more maxillary datasets will be added to the proposed network to improve the accuracy. Besides, a model for the mandibular datasets would be trained. Finally, the boundary of the teeth could be obtained after the segmentation and then applied to the 5-axis aligner trimming machine.

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