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Automatic Teeth Segmentation From Panoramic X-ray Images Using Deep Learning Models

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Short Bio of the Presenter

Dr. Shuaa S. Alharbi received a BSc and MSc in Computer Science from Qassim University, KSA, and her PhD also in Computer Science from Durham University, UK. She is currently working as Assistant Professor at Computer College, Qassim University, KSA

Her interdisciplinary research focuses on machine learning and image processing in biology and medical domains. In particular, she is interested in using deep learning to analyze medical images and improve the accuracy of disease diagnosis, which is a rapidly growing area of interest.

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Introduction

- Teeth segmentation and object detection are the core functions of these tools when applied to X-ray images.
- Segmenting and detecting the teeth in images is actually the first step in enabling other automatic processing methods.
- Medical image segmentation, especially in dentistry field, has been transformed by Deep Learning (DL) in recent years.

Introduction

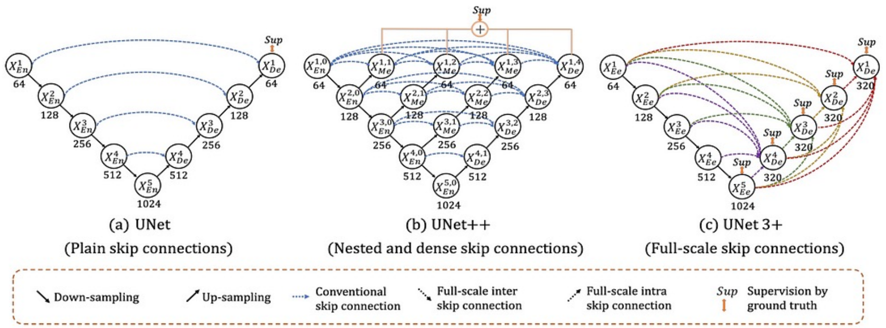
- In recent years, there has been increasing interest in applying the Deep Learning (DL) models for medical image analysis.
- The deep learning, typically the Convolutional Neural Network (CNN, or ConvNet) has made a significant contribution to the medical images analyzing tasks especially the segmentation.
- Semantic segmentation methods based on DL have demonstrated state-of-the-art performance over the past few years.
- In computer-assisted procedures topically aim to applied in dental clinics, teeth **segmentation** is an essential step.
- By using this technique, it is possible to provide approximate outline images of doubtful regions in order to provide features that can distinguish tooth tissues from other types of tissues.

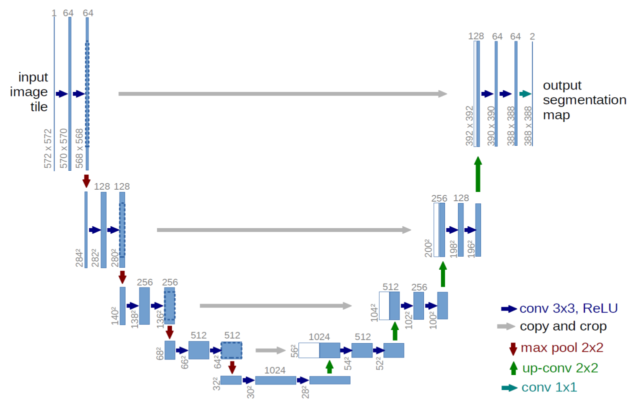
U-Net For Teeth Segmentation

- It has been demonstrated that these techniques have been successful in classifying, segmenting, and detecting medical images.
- For these applications, the U-Net[1] deep learning technique has become very popular.
- The U-Net shape with its variations and extensions (U-net++ [2], Resunet++[3]) has long been recognized as the dominant deep network architecture.
- In this regard, it is the most widely used architecture in the medical imaging segmentation field.

U-Net For Teeth Segmentation

- U-Net with its different extensions and modifications has been among the most popular deep networks developed for medical image segmentation.





- **However, it is difficult to determine which one will work best for teeth segmentation??**

Purpose:

- In this study, different semantic segmentation models are selected based on their common use in medical image segmentation.
- Models include:
  - U-Net++
  - ResU-Net++
  - MultiResU-Net.
- We evaluate the performance and segmentation accuracy of these models using a pre-request dataset provided by Intelligent Vision Research Lab (Ivisionlab).
- Based on the results presented in this paper, these methods can be used to improve the detection and segmentation of teeth in panoramic X-ray images.

Methodology

- The dentist uses panoramic radiographs to obtain an overview of the entire mouth and jaw, including all the teeth, in dentistry.

- It has been used to detect larger concerns like infections, impacted teeth, and tumors.
- There is a low resolution in panoramic radiography X-ray images, which contributes to noise in the images.

- To process dental X-ray images, it is necessary to distinguish between the ROI and backgrounds.

- In this research we compare 3 different CNN models that used regularly in medical image segmentation task and evaluate their results using a publicly available dataset.

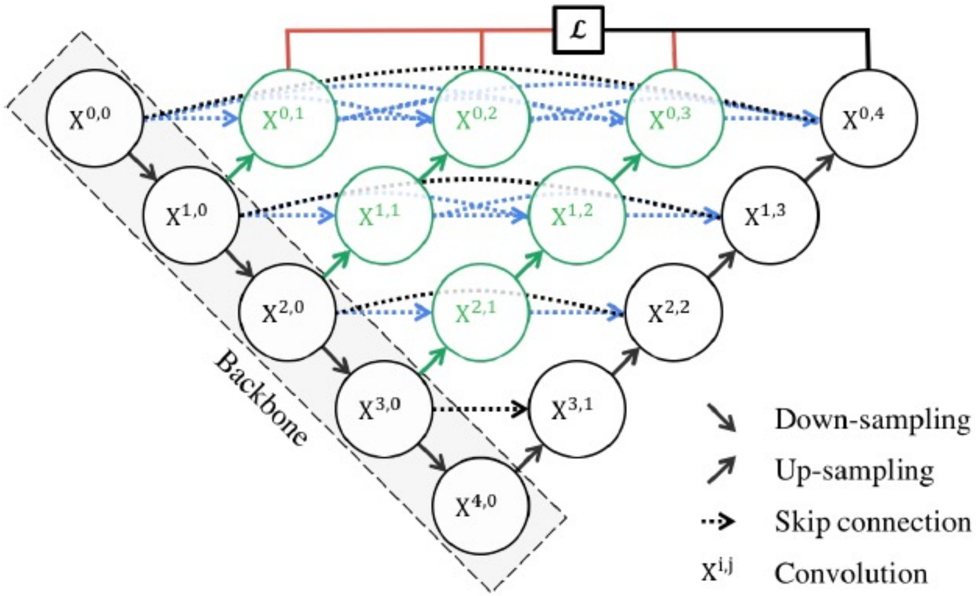
Methodology
1- Models Architectures Overview:

(1)- U-net++ Architecture:

- The U-net++ architecture [2] in terms of medical image segmentation, is a more powerful architecture.
- There are several nested, dense skip pathways connecting the encoder and decoder sub-networks in this architecture.
- As a result of the redesign of the skip pathways, the semantic gap between the feature maps of the encoder and decoder sub-networks is reduced.

Methodology
1- Models Architectures Overview:

U-net++ Architecture:



Methodology
1- Models Architectures Overview:

(2)- ResUNet++ Architecture:

- The ResUNet++ Architecture [3] is based on the Deep Residual U-Net (ResUNet) [4], which is a deep residual learning concept combined with an U-Net.

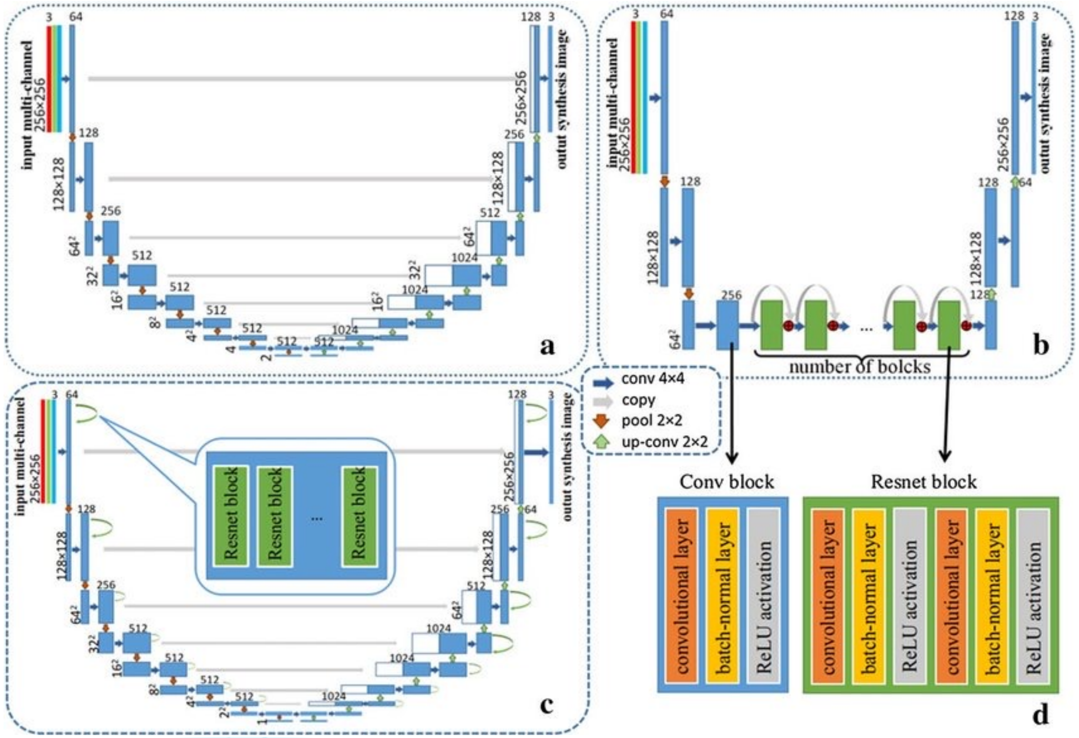
- There are three encoder blocks and three decoder blocks comprised of the ResUNet++ architecture.

- An encoder block comprises two successive convolutional blocks of 3 × 3 and an identity mapping.

- Consequently, channel interdependencies are improved while computational costs are reduced.

Methodology
1- Models Architectures Overview:

ResUNet++ Architecture:



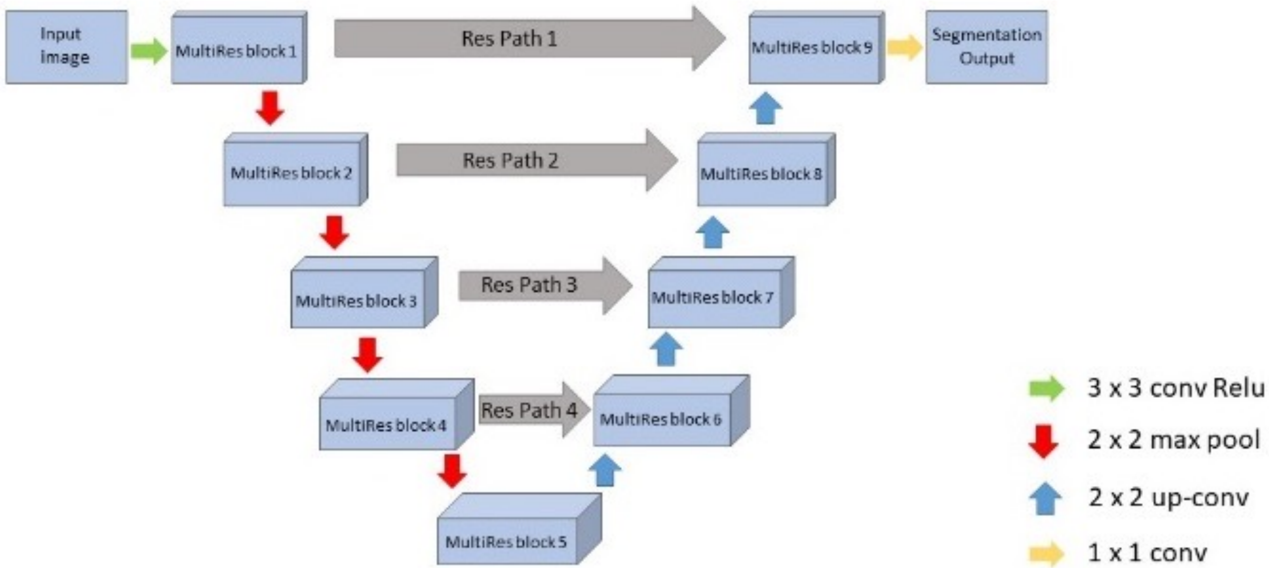
Methodology
1- Models Architectures Overview:

(3)- MutiResU-Net Architecture:

- In MutiResU-Net architecture [5], a MultiRes block is proposed as a replacement for two convolutional layers.
- The number of filters in the convolutional layers is controlled by a parameter within each MultiRes block.
- A MultiRes block has been proposed in order to enhance U-Net's capability to analyze and assess data at multiple resolutions.
- In some cases, there is a discrepancy between the features propagated through the encoder network and the features propagated through the decoder network.

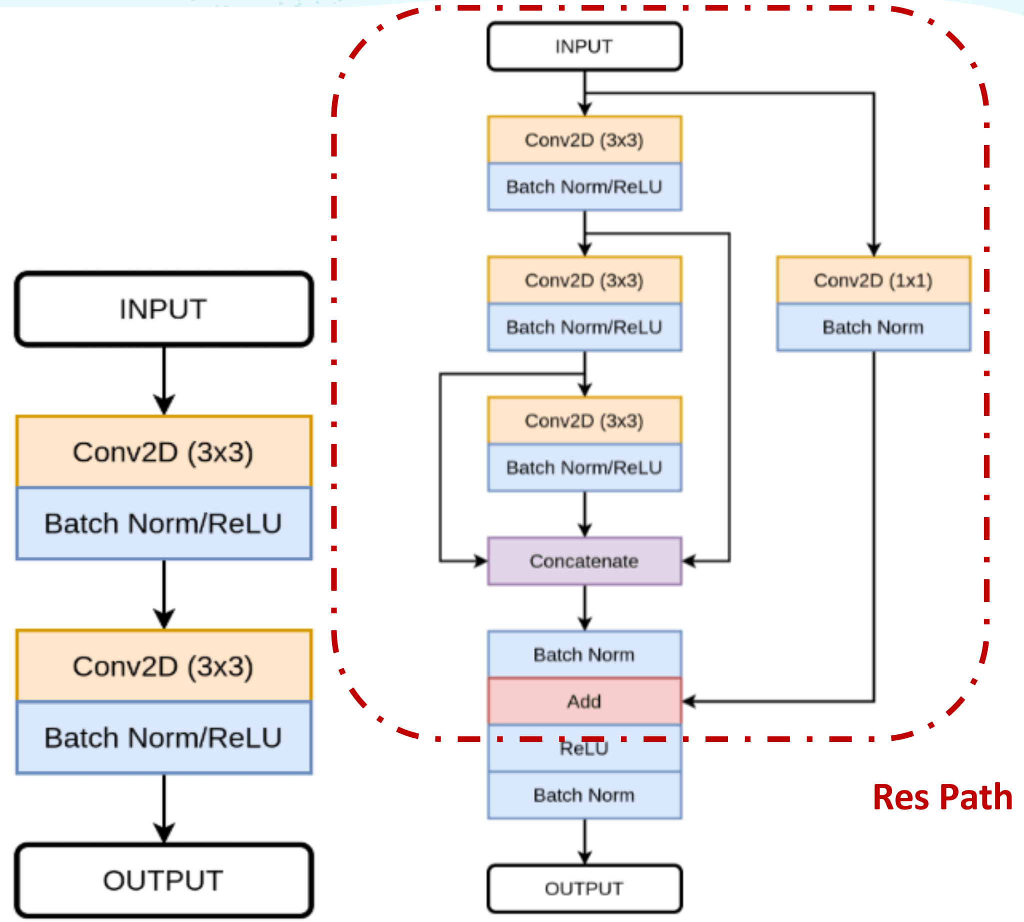
Methodology
1- Models Architectures Overview:

MutiResU-Net Architecture:



Methodology

MutiResU-Net Architecture:



Convolutional block in UNET **MultiRes block in MultiResUNET**

Methodology
2- Dataset and Ground Truth:

- It is noteworthy that panoramic X-ray images provide a greater degree of patient comfort than other radiographics, such as intraoral images (bitewing and periapical), and are less invasive, while examining a greater portion of the maxilla and mandible.

- For dental image analysis, only a few datasets of panoramic X-ray images are publicly available.

Methodology
2- Dataset and Ground Truth:

- The UFBA-UESC dental images dataset was published by Silva et al., [6] to fill this gap, and it has proven to be a valuable resource for the community. The original data set was published with annotations for semantic segmentation only, which utilizes binary masks to distinguish teeth from non-teeth pixels.

- Jader et al., [7] modified the UFBA-UESC Dental Images dataset to include instance segmentation information, and a total of 276 images containing 32 teeth were used for training and validation, with the remaining 1224 images being used for testing.

Methodology
2- Dataset and Ground Truth:

- Recently, Silva et al., [8] from Ivisionlab they annotated 543 images with number information (including the 276 used by Jader et al., [7]) to evaluate semantic segmentation.

- The dataset for this paper was obtained from Ivisionlab[1] [8] in order to perform our experiments .

- In this dataset, total of 1500 panoramic X-ray images with high variability have been grouped into ten categories in this dataset.

- A combination of panoramic X-ray images and ground truth images is included in this dataset.

[1] https://github.com/IvisionLab/dns-panoramic-images

Methodology

2- Dataset and Ground Truth:

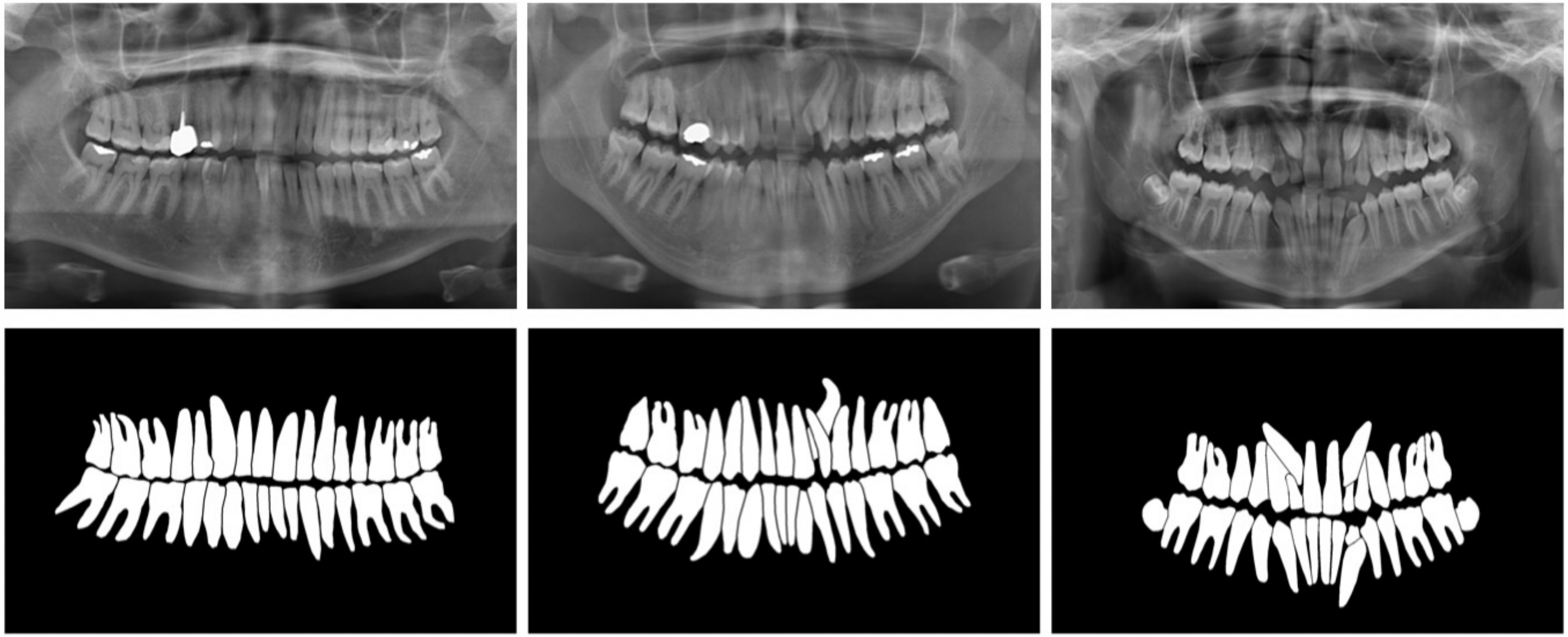


Figure 1: Three different simple panoramic X-ray images from Ivisionlab [6] alongside with their ground truth.

Evaluation and Assessment Metrics

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall (Sensitivity)} = \frac{TN}{TN + FP}$$

$$\text{F1-Measure} = \frac{2 \cdot TP}{2 \cdot TP + FP + FN}$$

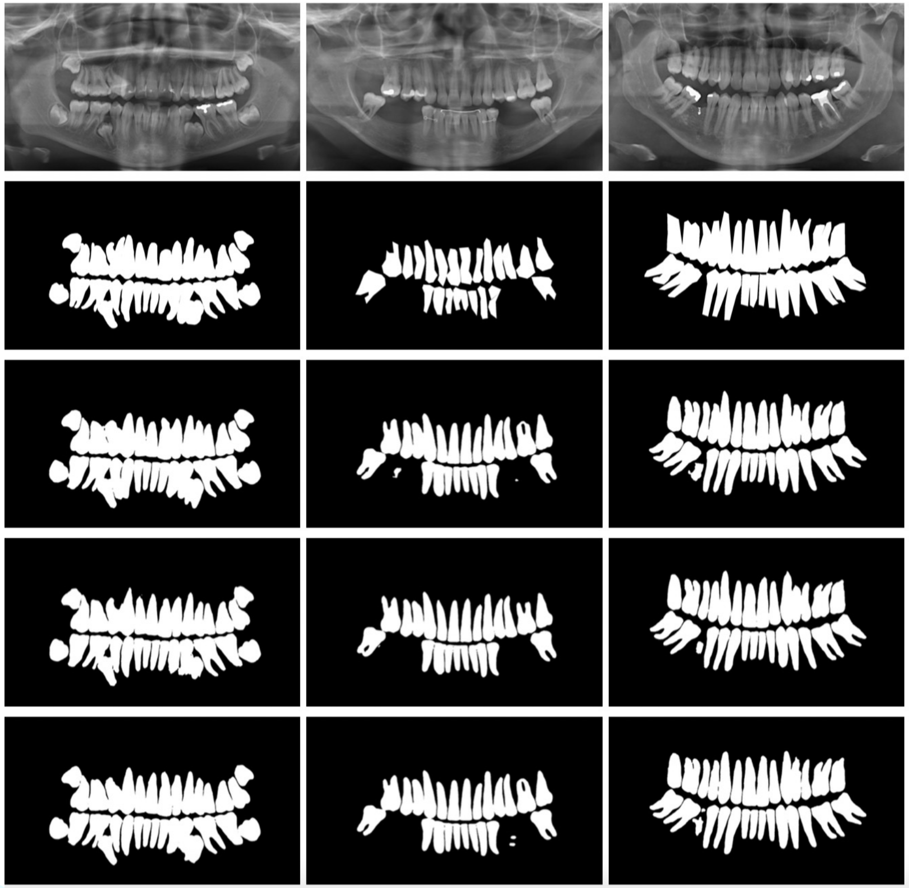
$$\text{F2-Measure} = \frac{TP}{TP + 0.2 \cdot 0.8FN}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Jaccard index} = \frac{TP}{TP + FN + FP}$$

Where TP is true positive, TN—true negative, FP—false positive, and FN—false negative cases.

Quantitative and Qualitative Comparison



- Qualitative analysis and comparison of the different CNN models using sample of panoramic X-ray images from IvisionLab dataset. Where:

- (First row): shows the original images,
- (Second row): ground truth,
- (Third row): U-Net++,
- (Fourth row): ResU-Net++ and
- (Fifth row): MultiResU-Net segmentation results.

Quantitative and Qualitative Comparison

- Quantitative comparison of different cnn modules applied to ivisionlab dataset:

CNN Model	Evaluation Matrix					
	Jaccard index	*Recall*	*Precision*	*Accuracy*	*F1-Measure*	*F2-Measure*
U-Net++	**0.8591**	**0.9228**	0.9273	0.9715	**0.9218**	**0.9217**
ResU-Net++	0.8501	0.9098	0.9283	0.9703	0.9161	0.9115
MultiResU-Net	0.8588	0.9162	**0.9339**	**0.9716**	**0.9218**	0.9176

* Bold font indicates the best value.

Finding

- It is noticable from Table I and Figure 2 that U-Net shape CNN models are quantitatively analyzed using IvisionLab data.
- It is notable that MutiResU-Net outperformed compare with other methods with accuracy of 97.16%.
- This is because MutiResU-Net performs better on heterogeneous datasets than classical U-Net.

EXPERIMENTS

The experiments were conducted using Python, more specifically Python3. Where in order to construct the network models, Keras was used with Tensorflow as the backend.

Conclusion and Future Work

- ✓ The results of our study indicate that MutiResU-Net may succeed the other U-Net architectures in the future, particularly when it comes to segmenting teeth from panoramic X-ray images.

Conclusion and Future Work

- ✓ This experiment and assumption relied on a single dataset for the evaluation of different models, which could explain why MultiResU-Net performed better.
- ✓ Future research should conduct experiments with different datasets to see whether this claim holds.

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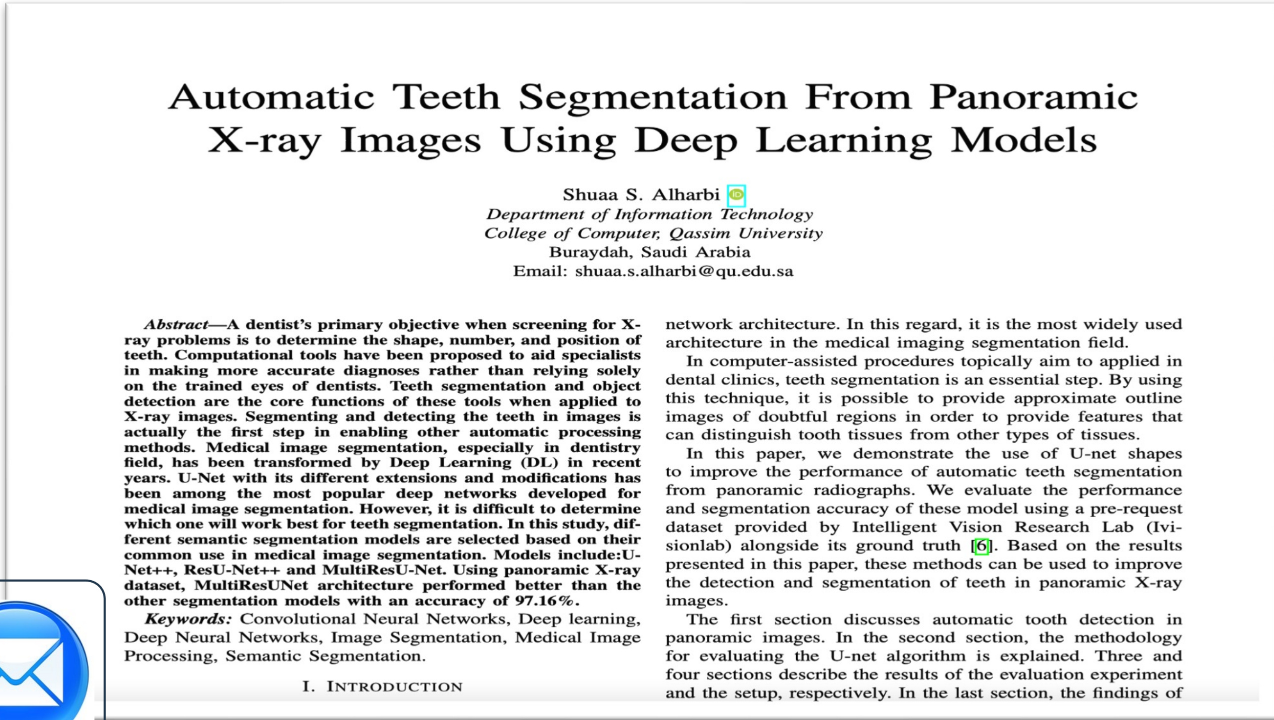

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***Abstract*—A dentist's primary objective when screening for X-ray problems is to determine the shape, number, and position of teeth. Computational tools have been proposed to aid specialists in making more accurate diagnoses rather than relying solely on the trained eyes of dentists. Teeth segmentation and object detection are the core functions of these tools when applied to X-ray images. Segmenting and detecting the teeth in images is actually the first step in enabling other automatic processing methods. Medical image segmentation, especially in dentistry field, has been transformed by Deep Learning (DL) in recent years. U-Net with its different extensions and modifications has been among the most popular deep networks developed for medical image segmentation. However, it is difficult to determine which one will work best for teeth segmentation. In this study, different semantic segmentation models are selected based on their common use in medical image segmentation. Models include:U-Net++, ResU-Net++ and MultiResU-Net. Using panoramic X-ray dataset, MultiResUNet architecture performed better than the other segmentation models with an accuracy of 97.16%.**

Keywords: Convolutional Neural Networks, Deep learning, Deep Neural Networks, Image Segmentation, Medical Image Processing, Semantic Segmentation.

I. Introduction

network architecture. In this regard, it is the most widely used architecture in the medical imaging segmentation field.

In computer-assisted procedures topically aim to applied in dental clinics, teeth segmentation is an essential step. By using this technique, it is possible to provide approximate outline images of doubtful regions in order to provide features that can distinguish tooth tissues from other types of tissues.

In this paper, we demonstrate the use of U-net shapes to improve the performance of automatic teeth segmentation from panoramic radiographs. We evaluate the performance and segmentation accuracy of these model using a pre-request dataset provided by Intelligent Vision Research Lab (Ivisionlab) alongside its ground truth [6]. Based on the results presented in this paper, these methods can be used to improve the detection and segmentation of teeth in panoramic X-ray images.

The first section discusses automatic tooth detection in panoramic images. In the second section, the methodology for evaluating the U-net algorithm is explained. Three and four sections describe the results of the evaluation experiment and the setup, respectively. In the last section, the findings of

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Thank You