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Original Article

Development of a Unified Deep-Learning Model for Dental Abnormality Examination Using Digital Photographs

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***Abstract** - Maintaining good Oral Health (OH) is important for an individual's general health. Clinical-level examination of the OH using recommended protocol is time consuming, and hence computerized algorithm-supported methods are commonly adopted in recent years. Owing to its increased accuracy, Deep Learning (DL) based OH testing has become a popular procedure in recent times. This study suggests a revolutionary Unified DL (UDL) technique that uses digital photos taken from actual patients to assess the state of the teeth. With a clinically meaningful level of accuracy, the suggested UDL model applies the DL scheme, for instance, segmentation, tooth recognition, and classification. Oral image collection, a novel UDL model-based assessment, DL-segmentation to extract the tooth and the caries section, and performance verification using the selected image database are the phases of this instrument. MIDNet18 serves as the foundation for three distinct UDL-schemes that are proposed in this study. Three distinct UDL-models can be achieved by combining MIDNet18 with the Region Proposal Network (RPN) and ResNet101. Metrics such as F1-score and error are used to validate the effectiveness of the suggested tool, and the results of the experiment show that the UDLII-model performs superior to other models taken into consideration in this investigation.*

***Keywords** - Digital photograph, Instance segmentation, MIDNet18, Oral Health, ResNet101.*

1. Introduction

Oral Health (OH) is a cornerstone of overall well-being, with implications extending beyond mere aesthetics to encompass systemic health. According to the report by the World Health Organization (WHO), oral diseases affect nearly 3.5 billion people globally (World Health Organization 2013), underscoring the magnitude of the public health challenge posed by dental issues [1]. Among these oral conditions, tooth decay, or caries, stands out as a prevalent and impactful chronic disease [2].

Traditional methods of detecting and segmenting teeth and caries in mouth photographs have faced considerable challenges. Hindering the accuracy of diagnosis and subsequent treatment [3]. Conventional techniques often rely on manual interpretation, leading to subjectivity and inconsistency in results. Furthermore, the limitations of two-dimensional imaging modalities can impede the comprehensive understanding of dental structures, particularly in complex cases involving overlapping teeth or subtle caries [4]. Accurate diagnosis is pivotal for effective treatment planning and patient outcomes in dentistry. Precise identification and segmentation of teeth and caries are fundamental steps in this process. Timely and accurate detection of dental issues enables early intervention, preventing the progression of conditions such as caries that, if left untreated, can lead to more extensive damage, pain, and the need for invasive treatments.

The major limitation of the existing method is the manual examination, which sometimes may lead to a manual error. Despite advancements in dental imaging, a critical gap persists in the realm of accurate and efficient detection and segmentation of teeth and caries from whole-mouth photographs.

Traditional dental imaging techniques, marked by manual interpretation and reliance on two-dimensional modalities, face inherent limitations that compromise the accuracy and efficiency of diagnosis. One apparent issue is the subjectivity introduced by manual interpretation, leading to inconsistencies in results and hindering the reproducibility of findings. The reliance on conventional two-dimensional imaging exacerbates this problem, particularly in cases involving overlapping teeth or subtle caries, where the spatial intricacies of dental structures are often inadequately captured.

Moreover, the inefficiencies of existing methods contribute to delayed diagnoses and may result in the oversight of early signs of dental issues. In the dynamic field of dentistry, where timely intervention is paramount, these shortcomings pose a significant obstacle to effective treatment planning and, ultimately, patient outcomes. The pressing need for a more refined and accurate approach to dental imaging becomes evident in the face of these limitations.

A novel instance segmentation technique emerges as a promising solution to bridge this gap, offering the potential to revolutionize the detection and segmentation of teeth and caries in mouth photographs. By addressing the shortcomings of traditional methods, this innovative approach holds the key to unlocking new horizons in precision, efficiency, and, ultimately, improved oral health outcomes. These innovative approaches reduce limitations in traditional techniques, offering enhanced precision and efficiency in the detection and segmentation of teeth and caries from Digital Teeth Photographs (DTP) [5].

Access to high-quality dental treatment is still a problem for those living in rural areas worldwide. This study fills this gap by using the Unified Deep Learning (UDL) Model in the creation of mobile applications. The ultimate objective is to provide people in rural areas with the tools they need to proactively monitor their dental health through an approachable and user-friendly platform.

This research aims to build a novel DL tool for classification and full-set tooth segmentation from the DTP considered in this research. Further, it also helps in detecting the tooth-caries with better precision.

The different stages present in the proposed UDL-model-based DTP examination include,

1. Image collection using a digital camera,
2. Implementing the automatic classification and segmentation of teeth using the DL model, and
3. Performance verification and confirming the clinical significance of the proposed tool.

In this research, MIDNet18 [6] is chosen as the backbone to construct the UDL model. The MIDNet18 combined with the Region Proposal Network (RPN) and the ResNet101 (RN101) helps in constructing three different UDL-models (UDLI to UDLIII), and the performance of the developed models is separately evaluated on the chosen image database.

Its performance is verified by considering the necessary metrics like mean-Average-Precision (mAP), mean-Average-Recall (mAR) and F1-Score (F1S). Based on these values, the performance of the proposed tool is confirmed. The investigation of this research authorises that the UDLII-scheme helps in obtaining smaller losses compared to the UDLI and UDLIII. The main contribution of this research involves;

1. Development of novel UDL models for digital tooth photograph examination,
2. Implementing a single DL scheme for the tooth and caries section,
3. Clinical significance verification of the developed UDL scheme using the clinically collected digital images.

Another part of this study is arranged as follows: Section 2 presents context, Section 3 demonstrates methodology, and Sections 4 and 5 show the experimental outcome and conclusion.

2. Literature Review

Maintaining the OH is essential, and any abnormality in the mouth will lead to various health issues. Hence, a number of schemes are proposed by the researchers for detecting tooth abnormalities using various imaging modalities which provide complete information about the oral cavity and the tooth. Imaging plays a chief role in dentistry for OH monitoring and it provides necessary results for the abnormality detection and treatment planning [7].

The availability of the high-performance camera also paved the way for a new imaging scheme, which can be considered to examine the general OH by analyzing the tooth and its healthiness, as discussed in the recent literature [8, 9]. The digital photographs help to collect the necessary sections, including the whole teeth section, and it is then examined using a chosen AI scheme.

The earlier research works implemented the DL techniques to support the disease detection and instance segmentation tasks, which helps the dentist to identify the nature of the tooth abnormality, and the exact location and identification of the tooth. This information will support in planning the appropriate treatment to overcome the dental issue.

Table 1 presents the summary of a few chosen tooth examination methods associated with tooth instance segmentation using a chosen DL technique.

Table 1. Summary of DL-supported tooth segmentation

Reference	Methodology	Evaluation Metrics		
		mAP	mAR	F1S
Qi et al. [10]	This work implements a DL model, PointNet, for classification and segmentation from 3D images.	0.73	0.65	-
Le et al. [11]	This work proposed a novel PointGrid scheme using the DL-like architecture for 3D shape recognition.	0.75	0.70	-
Hermosilla et al. [12]	This work proposed a novel Monte Carlo convolution to improve the performance in the conventional DL model.	0.88	0.84	-
Li et al. [13]	A novel DL model known as PointCNN was invented to implement the convolution on x-transformed points.	0.87	0.83	-
Zanjani et al. [14]	Development of a novel DL model; PointCNN++ is presented in this work for implementing segmentation on 3D teeth scan images.	0.93	0.90	-
Liu et al. [15]	Multi-scale Affinity with Sparse Convolution (MASC) was suggested in this work as a way to segment 3D pictures.	0.92	0.89	-
Zhou et al. [16]	This research proposed VoxelNet for point cloud-assisted 3D object recognition.	0.92	0.91	-
He et al. [17]	This work proposed a Mask R-CNN (MRCNN) model for automatic object detection.	0.96	0.97	-
Zanjani et al. [18]	Suggested a new DL model for segmentation with Mask-MCNet for 3D teeth scan images.	0.98	0.97	-
Yuan et al. [19]	Proposes full-set tooth segmentation using PointNet.	0.94	0.92	0.93
	Proposes full-set tooth segmentation using PointCNN.	0.97	0.91	0.94
	Proposes full-set tooth segmentation using PointNet++.	0.97	0.95	0.96
	Proposes full-set tooth segmentation using improved PointNet++.	0.98	0.97	0.98

The metrics in Table 1 confirm that the earlier works found in the literature on tooth segmentation in 3D teeth images offered better values of mAP (98%), mAR (97%) and F1S (98%) on the synthetic images.

The major research gap in DL-based teeth and their abnormalities detection is that the earlier works are not validated on the real clinical teeth images, and their outcome is not verified clinically. Further, the existing earlier works utilized a 3D image-based examination of the tooth sections, which is quite difficult to capture.

Also, it needs complex methodologies when implemented in real time. Hence, the proposed research aims to propose and implement a simple, cost-effective and clinically approved procedure to diagnose the complete OH using the DTP collected with a chosen digital camera. Compared to the earlier works in the literature, the proposed technique is simple and provides better results for classification, tooth identification, and instance segmentation operations. To overcome the difficulties in the earlier research and also to propose a simple and affection methodology, this research considered the DTP recorded using a conventional digital camera. The tooth region in the DTP is then examined for classification and segmentation as in the earlier methods presented in Table 1, and the performance is evaluated and confirmed. The major merit of the proposed research is that it considers the DTP collected from real patients, and the achieved outcome of this study is verified and confirmed by the dentists.

3. Materials and Methods

Dental caries detection and classification in oral maxillary images represent a critical aspect of modern dental diagnostics. In this study, an innovative approach to advance accuracy in teeth classification, detection, and segmentation is presented.

Leveraging the UDL model integrated into the Mask R-CNN framework, the proposed technique aims to enhance the precision of identifying dental caries, providing a more advanced solution compared to existing techniques. The different schemes available in the developed UDL model are presented in Figure 1. The necessary images are collected using the digital camera. After collecting the necessary DTP, the classification and segmentation task is executed using the proposed UDL model and the outcome of the system is then verified with the Ground-Truth (GT) developed using ITK-Snap [20, 21]. After that, the segmented part is checked against the GT, and the required metrics are found. The created UDL model's value is used to prove its worth.

3.1. Data Collection

This study utilizes DTP to train and evaluate the proposed UDL model. The MIDNet18 discussed in [6] serves as the primary feature extractor and acts as the backbone for the UDL model in this study. To verify the performance of the developed tool, the necessary DTP are collected from the real patients using a digital camera.

The image collection involves the following phases: patient screening using visual inspection, getting permission from the patients to record and examine the oral section using digital images, obtaining informed consent from every volunteer who agrees to participate in this research work, implementing the necessary clinical protocol during the oral section image collection, getting the ethical clearance from IHEC, and executing the proposed work. The proposed scheme is a non-invasive method, and it needs only a digital image of the oral region to complete the OH examination task.

This study strictly followed the guidelines of the Institutional Human Ethical Committee (IHEC) of Saveetha Dental College and Hospital, Saveetha Institute of Medical and Technical Sciences (SIMATS) and having the IHEC approval number of “IHEC/SSE/FACULTY/22/EGG/337”. During this study, 500 volunteers are screened after implementing the recommended oral cleaning protocol; teeth cleaning and drying. The images collected with a DSLR Camera (Nikon D5600: AF-P 18-55mm + 70-300mm VR Lens) are then considered for the experimental investigation.

The sample images available in this database are depicted in Figure 2. In which Figure 2(a) shows a healthy-case, and Figure 2(b) presents caries-case. These images are then considered for evaluation using the proposed UDL-models.

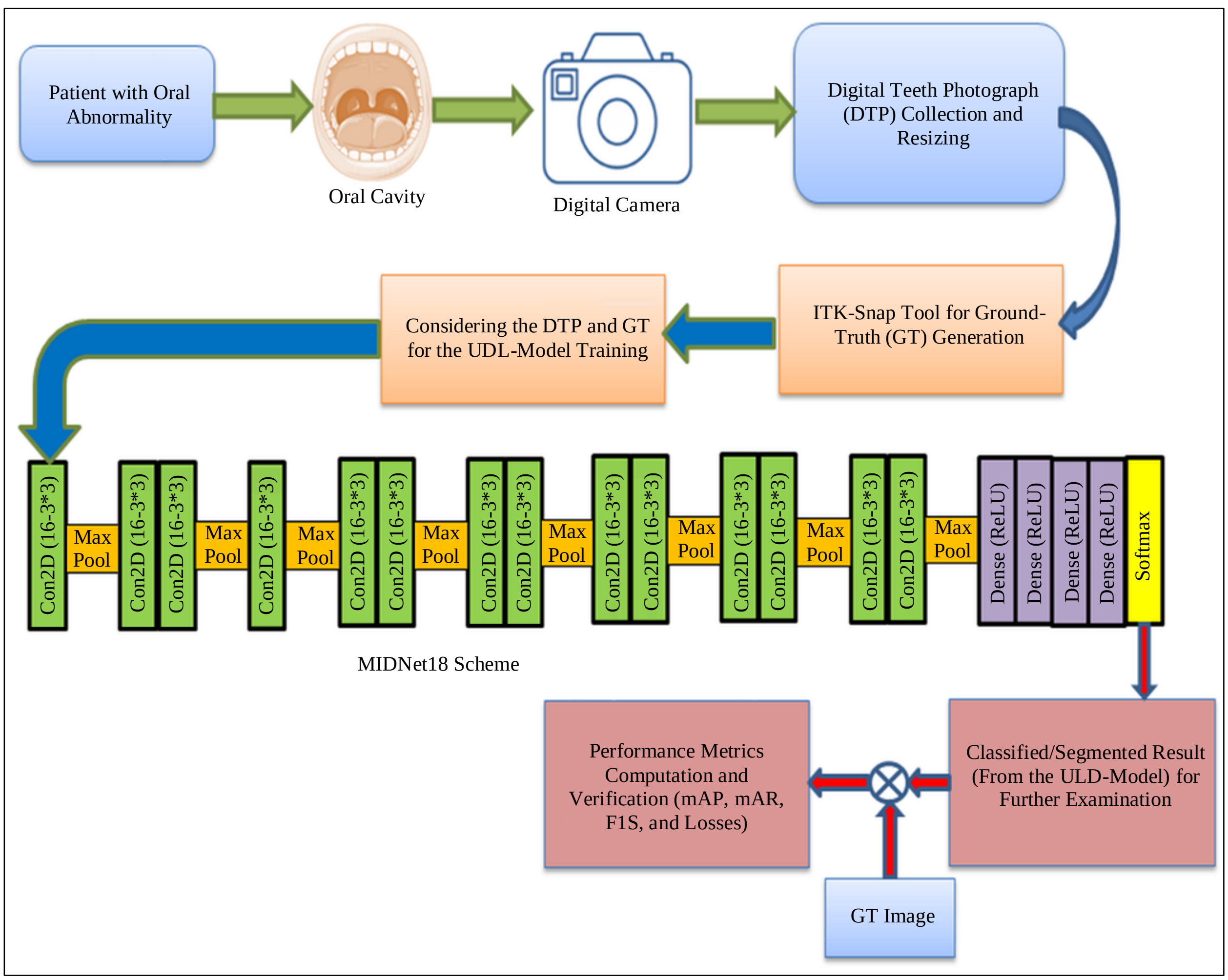


Fig. 1 Automatic tool and carries detection using UDL-model

(a) Healthy **(b) Caries**

Fig. 2 Sample DTP collected from volunteers

3.2. UDL-Model Specification

This work proposes the UDL model by considering the MIDNet18 as the backbone, and the necessary information about the MIDNet18 can be accessed from [6]. The MIDNet18 is a simple and effective technique to extract the features from the chosen digital images and in this work, it is considered to evaluate the healthy and caries DTP. Also, it provides the necessary support for instance segmentation. The proposed UDL model consists of two stages;

Stage 1: Feature extraction and Bounding-Box (BB) proposal to support full-set tooth segmentation. The operations in Stage 1 are as follows;

- Input images are fed into the MIDNet18 CNN model for the feature extraction process,
- Instantaneously, the feature map from MIDNet18 is provided to both the Region Proposal Network (RPN) and the ResNet101 (RN101) model.

Stage 2: Implementation of simultaneous classification, object detection, and instance segmentation, as discussed below;

- Proposals from the RPN layer and the CNN backbone are directed to the RoIAlign [21].
- RoIAlign utilizes bilinear interpolation and non-max suppression to fix feature map size and select bounding boxes based on a predefined threshold.
- Features and region proposals from RoIAlign are then sent to the fully connected branch and mask branch for simultaneous classification, detection, and instance masking.

The obtained results in this study are verified by computing the necessary metrics, like mAP, mAR, and F1S. The different schemes considered in the developed UDL-models consist of the following;

- UDLI consist model with a modification by MIDNet18 to ResNet101 + MIDNet18 to RPN
- UDLII consist model with a modification by MIDNet18 to RPN+ ResNet101
- UDLIII consist MIDNet18+ResNet101

3.3. Model Comparison and Performance Metrics

The performance of the proposed UDL-models (UDLI, UDLII, and UDLIII) is then compared against the MRCNN combined with RN50/RN101. Ground-truth annotations prepared using the ITK-Snap [20, 21] are chosen as a benchmark for evaluating the achieved result.

Initially, the necessary metrics, like mAP, mAR and F1S, are chosen to examine the merit of the UDL-models, and the mathematical expression can be found in [6]. Along with these initial metrics, other necessary loss values are also considered for the verification, as discussed in [22].

- RPN Loss Function: The mathematical form of this loss is presented in Equation (1);

$$L(\{prob_i\}, \{V_i\}) = (1/N_c) \sum L_c (prob_i, prob_i^*) + \lambda (1/N_R) \sum_i prob_i^*) L_R (V_i, V_i^{\wedge}) \quad (1)$$

Here, i-denotes the anchors, prob is the probability of detection, V is predicted Bounding-Box (BB), and N_c & N_R are normalization values.

- MRCNN Loss Function: The mathematical form of this loss is presented in Equation (2);

$$L_t = L_c + L_b + L_m \quad (2)$$

Here, L_t= model's total cost function, L_c = classification loss, L_b= regression loss, and L_m= average binary cross-entropy loss. Other related values are presented in Equations (3) to (5).

$$L_c (prob_i, prob_i^*) = -lb [prob_i, prob_i^* + (1- prob_i)(1- prob_i^*)] \quad (3)$$

Where $prob_i$= predicted probability of anchor point i, $prob_i^*$= predicted value of the corresponding ground truth, and lb = log loss function.

$$L_b (V_i, V_i^*) = R (V_i - V_i^*) \quad (4)$$

Where R= robust loss function, V_i = parameterized of 4 coordinate vectors of the predicted frame, V_i^*= vector coordinate corresponding to the border of the ground truth.

$$L_m = -1/x \sum_i [a_i^* \log prob (a) - (1-a) \log (1-prob (a))] \quad (5)$$

Where a= number of pixels, a_i^*= label class of the pixel located, and prob (a) = probability.

The above-discussed measures are considered to verify the performance of the developed tool while examining the chosen DTP.

3.4. Prime Metrics for the Performance Evaluation

Along with the UDL-model metrics, the evaluation outcome is also verified using the prime metrics, like mAP, mAR, and F1S, as discussed in [19]. These measures help in providing the overall performance of the developed scheme and based on its values, the significance of the developed system is confirmed.

Further, the clinical significance of this scheme was also verified by an experienced dentist (refer to acknowledgement) who checked and confirmed the outcome of the developed UDL model in evaluating the real patient data.

4. Result and Discussion

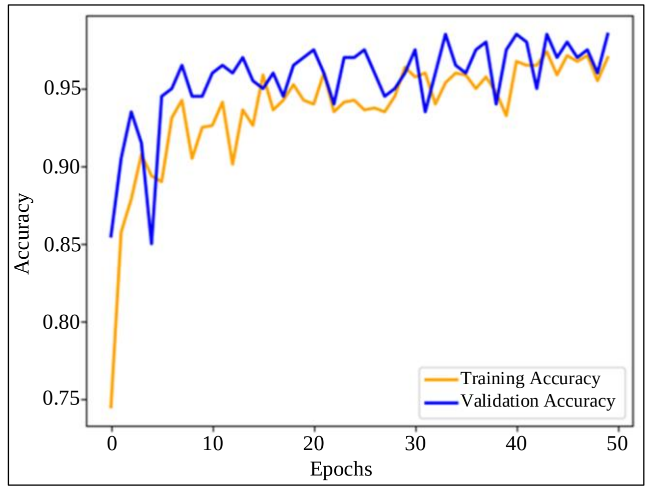
All experiments were conducted on a MacBook Air with an M1 chip and 8 GB RAM. The models were trained on a GPU using Google Colab Pro for 50 epochs. A learning rate of 0.1 and a learning momentum of 0.9 were maintained across all models. This study aims to not only improve dental caries detection but also contribute valuable insights into the efficacy of the proposed UDL models compared to established methodologies.

The performance of the developed tool is trained using 80% images and validated using 10% images. The remaining 10% of data is then considered to test the performance of UDL-models of this research. The initial training outcome achieved for the UDLI is depicted in Figure 3.

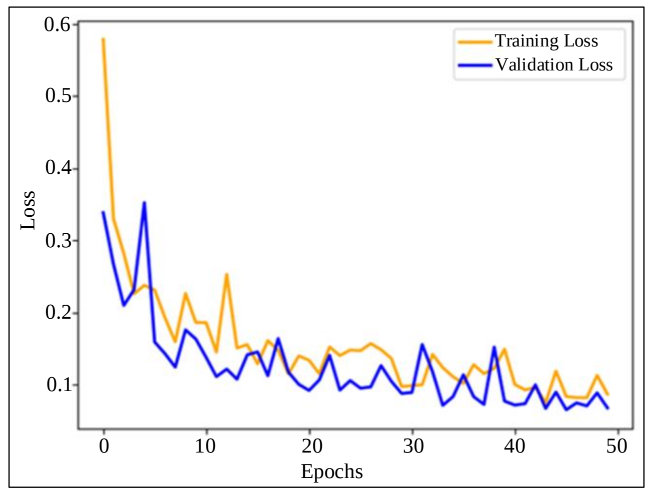
Figure 3(a) presents the accuracy Vs epochs, and Figure 3(b) shows the loss Vs epochs. These results confirm that the training accuracy is better with the UDLI on the chosen image database. A similar task is repeated with other models, and the achieved results are recorded.

After the training, the testing task is then executed on a chosen DTP, and the attained results are recorded and verified. Figure 4 presents the full-set tooth segmentation using the proposed UDL-models and the achieved results for tooth and caries detection. Figure 4(a) shows the chosen test image for the examination, which consists of 14 clearly visible teeth (healthy and caries). The proposed model must detect the tooth and its abnormality using BB detection along with instance masking.

Figure 4(b) shows the result of UDLII, which clearly detects 11 teeth, marks it as a healthy class and ignores the caries. Figure 4(c) presents the outcome of UDLII, which detects all 14 tooth segments along with the caries mask; Figure 4(d) confirms the detection of 12 teeth and caries when UDLIII is implemented. From these results, it is confirmed that the ULDII performs well on the chosen model. Then, to see how good this model is, the segmented part is compared to the Ground Truth (GT), and the right metrics are found, as shown in Table 2.



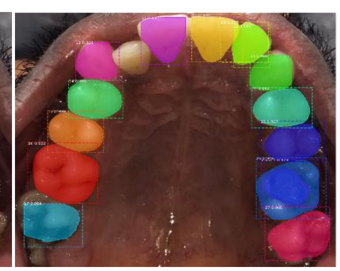
(a) Accuracy



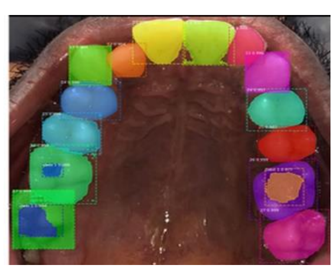
(b) Loss

Fig. 3 Training and validation outcome for UDLI

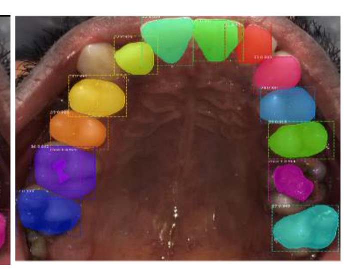
(a) Test image



(b) UDLI



(c) UDLII



(d) UDLIII

Fig. 4 Experimental investigation of UDL-models using a chosen DTP

(a) MRCNN+RN50 **(b) MRCNN+RN101**

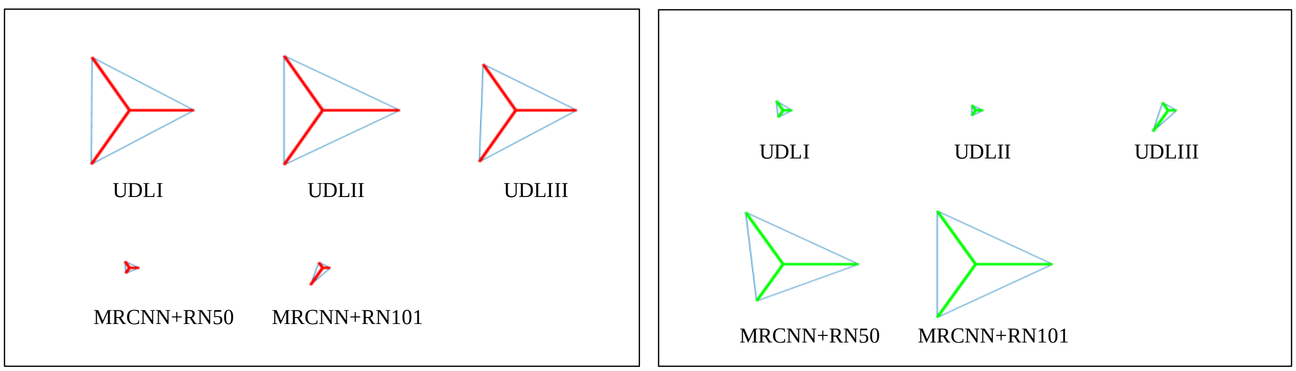
Fig. 5 Experimental investigation with MRCNN with RN50/RN101

The overall outcome of the proposed study is presented in Table 2 and this confirms the performance of UDLII. Table 2 presents the metrics considered in this research, along with the loss values in each DL model for the classification and segmentation of the chosen DTP. The mean of the measures computed in this research confirms that the UDLII presents better results compared to the alternatives.

A Glyph-plot is made for the quality metrics and the loss, as shown in Figure 6, so that the results can be checked visually. Figure 6(a) presents the plot for the metrics, and Figure 6(b) shows the plot for the loss. The overall metrics by the UDLII us better (larger occupied area in the plot) than other techniques, as in Figure 6(a), and also superior (small occupied area in the plot) than the similar and the MRCNN models. This confirms the merit of the UDLII for the clinical grade examination of the DTP collected from real patients.

Table 2. Overall performance achieved using the test DTP database

Model	mAP	mAR	F1S	RPN Loss	MRCNN Loss	Mask Loss
UDLI	0.9671	0.9935	0.6736	0.1935	0.1152	0.1823
UDLII	0.9866	0.9966	0.6752	0.1876	0.1010	0.1731
UDLIII	0.9615	0.9781	0.6659	0.1910	0.1096	0.2634
MRCNN+RN50	0.8825	0.8915	0.5227	0.4783	0.2563	0.3524
MRCNN+RN101	0.8793	0.8893	0.5593	0.4842	0.2608	0.4465



(a) Performance Metrics **(b) Loss**

Fig. 6 Glyph=plot for the overall performance verification

To verify the overall merit of the proposed UDL-models, the mAP and mAR values are then compared against the best earlier research works presented in Table 1 [17-19]. This comparison is presented in Figure 7. This comparison also verifies that the proposed UDLII-model provides a comparatively better result than other chosen models. The performance of the developed UDL-models is then compared against the recent DL segmentation results by Yuan et al. [19], and this comparison also confirms that the proposed UDL-models help to achieve better results compared to the results of the PointNet and its recent variants.

The graphical comparison depicted in Figure 7 confirms that the mAP and mAR of the UDLII are superior. The proposed work implemented the UDL model to analyse the DTP collected from the patients using a chosen digital camera. In future, the DL model of this scheme can be replaced with the lightweight DL models in order to develop and implement a mobile-phone-supported examination app for real-time OH monitoring and tooth and caries segmentation.

The major merit of the proposed research is that it uses a digital camera-supported technique to examine the OH, which is a simple and cost-effective approach. The main limitation is, that preparing the patient, capturing the image with better quality, resizing, and evaluation are quite time-consuming. In the future, the MIDNet18 can be replaced using the MobileNet technique, and a mobile application-based image collection, evaluation, and abnormality detection can be proposed to simplify the OH examination task.

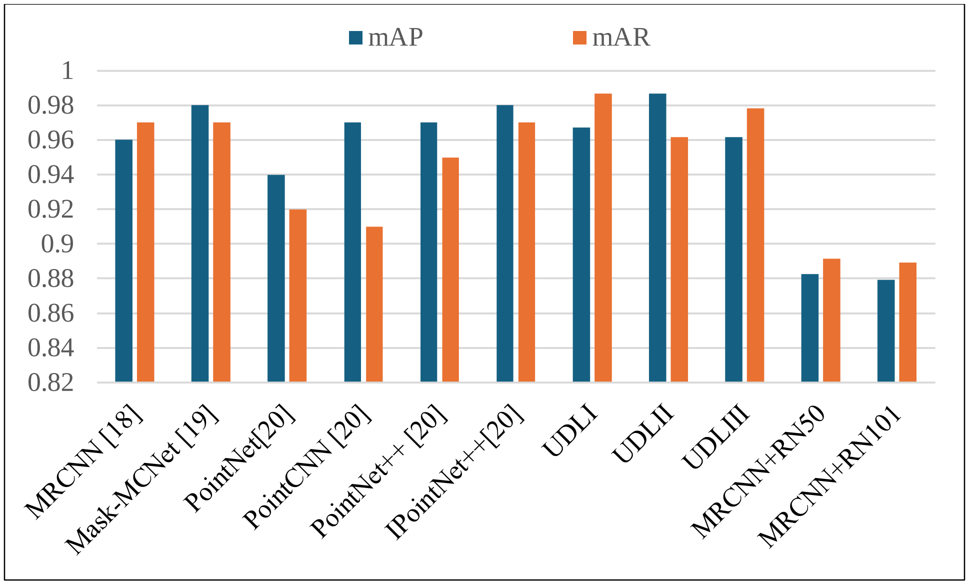


Fig. 7 Evaluation of mAP and mAR with earlier research works

5. Conclusion

This research work aims to develop a simple tooth and caries detection system to ensure the OH. The earlier works existing in hospitals need complex imaging and examination methods to detect dental abnormalities. In order to support a faster diagnosis and treatment, this research proposed novel UDL-models for classification and segmentation of the tooth in the DTP.

The developed tool utilizes the MIDNet18 scheme as the backbone, and to implement the segmentation, it also includes a hybrid architecture using RPN and RN101 schemes. This research developed three different UDL models and the performance of these models is verified against the MRCNN+RN50 and MRCNN+RN101 techniques.

Further, the merit of the developed technique is also verified against the similar models found in the literature. The outcome of this research confirms that, the UDLII-model helps in achieving better values of mAP, mAR, F1S, and loss values compared to the alternatives. In future, the conventional DL scheme will be replaced with the lightweight DL models to develop and implement a mobile-phone supported UDL-model for the DTP examination task.

Ethical Clearance

Informed concert is obtained from each volunteer who participated in the data collection process. This work was also approved by the Institutional Human Ethical Committee (IHEC) of Saveetha Dental College and Hospital, Saveetha Institute of Medical and Technical Sciences (SIMATS) and having the IHEC approval number of “IHEC/SSE/FACULTY/22/EGG/337”.

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Data Availability Statement

The clinical data supporting the findings of this study are available upon reasonable request from the first author.

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