UE20CS390A – Capstone Project Phase – 1

Project Progress Review #2
(Project Requirements Specification and Literature Survey)

Project Title : Redefining Dental Radiology using Deep Learning
Project ID : PW23_VRB_03
Project Guide : Prof. V R Badri Prasad
Project Team : Kshitij G.Saha, Pratham Kulkarni, Animesh Agarwal, Dheeraj R P

Abstract

Dental X-rays are one of the primary means for dentists to diagnose a multitude of dental ailments, abnormalities, structural anomalies, and diseases. A second utility of dental imaging also lies in the field of biometrics. Countless conditions like Dental decay, Periodontal disease, Mesioangular impaction, Periapical abscess, Horizontal bone impaction, Vertical bone impaction Apical periodontitis, Overhanging restoration, Irreversible pulpits, Cast post-restoration, Radiopaque restoration, Proximal caries are detected using an X-ray. Currently, dental X-ray diagnosis is still done manually by experienced clinicians but it is time-consuming, arduous, and also prone to human errors. To solve this issue, image segmentation, image enhancement, and machine learning are being considered to automate this process and make it more seamless and faster, saving countless man-hours and providing accuracy. Implementation of this solution would include dataset generation, image preprocessing, model building, hyperparameter tuning, and deployment. The exact number of classes that can be detected/classified will be determined based on discussions with subject matter experts.

Suggestions from Review - I

- Making the project name more specific
- Being in regular touch with subject experts
- Introducing noise to some X Rays to account of distorted images

Constraints / Dependencies/ Assumptions / Risks

- Legal implications for using proprietary data: removing personal data of all images
- Constraints: limited availability of dataset
- Assumptions: X Ray images are taken on devices without any distortions or noise
- Dependencies: on dental practitioners for provision of dataset and expertise

Functional Requirements

1. Image Import: The software should allow for the import of OPG and lateral cephalogram X-ray images in various formats, including DICOM, JPEG, and PNG.
2. Image Preprocessing: The software should preprocess the images to enhance their quality and remove noise, which can affect the accuracy of the detection and classification algorithms.
3. Detection and Localization: The software should be able to automatically detect and localize dental diseases and anomalies, such as caries, periodontitis, and impacted teeth.
4. Annotation: The software should automatically annotate the detected abnormalities with appropriate labels and visual indicators, such as bounding boxes or arrows, to indicate their location and type.

Functional Requirements

5.Classification: The software should classify the detected abnormalities based on their type and severity, such as mild, moderate, or severe.

6.Integration with Electronic Health Records: The software should integrate with electronic health records (EHRs) to store and retrieve patient information, including X-ray images and corresponding annotations.

7.User Interface: The software should have an intuitive user interface that allows users to view and interact with the annotated X-ray images, adjust detection and classification parameters, and export results.

8.Training and Support: The software vendor should provide training and support to users, including documentation, online tutorials, and technical support to ensure that the software is used effectively and efficiently.

Non-Functional Requirements

1. Reliability: The software should be reliable, with high uptime and availability, and able to handle hardware and software failures gracefully.
2. Scalability: The software should be scalable, able to handle increasing volumes of data and users without compromising performance or accuracy.
3. Compatibility: The software should be compatible with various operating systems, browsers, and devices, and integrate seamlessly with other dental imaging software and electronic health record systems.
4. Usability: The software should be easy to use, with an intuitive user interface and minimal training required for users.
5. Security: The software should be secure, with strong encryption and access controls, and compliant with data protection regulations
6. Interoperability: The software should be interoperable, able to exchange data and communicate with other dental imaging and analysis software, as well as external databases and applications.
7. Ethical considerations: The software should take into account ethical considerations such as fairness, transparency, and accountability in its algorithms and data handling processes.

Analysis of Deep Learning Technique for Dental Informatics: A Systematic Literature Review

Published: 28 September 2022

Abstract:

This study provides a solid foundation for a **thorough and critical examination** of modern DL-based digital dentistry technology and dental disease diagnostics. It advocates a systematic review approach that will assist upcoming scholars in figuring out the general framework of a dental diagnostic based on DL. This research provides a **detailed picture of the deep neural network designs** used in several DI areas to identify dental diagnostics

- **Why Dental Informatics (DI) is needed?**

DI provides a variety of **tools, visualization and applications** for the purpose of clinical practice of the **oral diagnosis** of illnesses, indications and prescription of particular medications to patients with particular problems, and other areas.

- **The current paper aims at answering the following research questions:**

#1: What are the existing DL techniques used in dental practice?

#2: Which categories of DI are adopting to use for the DL techniques?

#3: Which type of images and datasets are used in dental informatics along with DL techniques?

#1: What are the existing DL techniques used in dental practice?

- Artificial Neural Networks (ANNs)

Authors Name and Year	Methods	Results	Authors Suggestions/Conclusions
Faria et al., (2021) [41]	Custom-made ANN	Detect accuracy = 98.8%, predict accuracy = 99.2%, AUC= 0.9886, 0.9869	This approach may be beneficial for detecting and predicting the RRC's development in other photos.

- Recurrent Neural Networks (RNNs)

Authors Name and Year	Methods	Results	Authors Suggestions/Conclusions
Alarifi and AlZubi, (2018) [51]	MSGSRNN	Accuracy = 99.25%, sensitivity = 97.63%, specificity = 98.28%	Outlined methodology analyzes patient characteristics and aids to know the failure and success rate of the process of implant treatment

- Convolutional Neural Networks (CNNs)

Schlickenrieder et al., (2021) [95]	pre-trained ResNeXt-101–32x8d	accuracy = 98.7%, AUC = 0.996	More training is needed in AI-based detection, classification of common and uncommon dental disorders, and all types of restorations.

- Generative Adversarial Networks (GANs)

Authors Name and Year	Methods	Results	Authors Suggestions/Conclusions
Kim et al., (2020) [99]	CNN, GLCIC, Edge Connect	Improvement of 0.004 mm in the tooth segmentation	The segmentation approach for complete arch intraoral scan data is efficient, time-saving, and as accurate as a manual segmentation method.
Kokomoto et al., (2021) [100]	PGGAN	p value < 0.0001	The quantity of trained photos has a significant impact on PGGAN's ability to generate realistic visuals.

- Graph Neural Networks (GNNs)

Zheng et al., (2022) [103]	Modified Dynamic Graph CNN (DGCNN)	mIoU = 97.49, accuracy = 98.94	The proposed teeth segmentation is robust to rotten, missing, crowded, and ectopic-tooth cases.

#2: Which categories of DI are adopting to use for the DL techniques?

- Computer Aided Design (CAD)/Computer Aided Manufacturing (CAM)

Xu et al., (2018) [114]	Customized CNN	Accuracy = 99.06%	It directly satisfies the industrial clinical treatment demands and is also robust to any possible foreign matters on dental model surface.

- Three-Dimensional (3D) Printing: 92.6%
- Electronic Dental Records (EDR)

Cui et al., (2021) [120]	Extreme Gradient Boost (XGBoost) algorithm	Accuracy = 96.2, Precision = 86.5, Recall = 83.0	ML methods showed promise for forecasting multiclass issues, such as varying therapies depending on EDRs.

- Cone Beam Computed Tomography (CBCT)

Miki et al., (2017) [124]	AlexNet network	Accuracy = 91.0%	Automated filling of dental data for forensic identification can benefit from the suggested tooth categorization approach.

- Virtual Reality (VR)/Augmented Reality (AR)/Mixed Reality (MR)

#3: Which type of images and datasets are used in dental informatics along with DL techniques?

Image Type	No. of Studies	Studies References
Radiographic images	25	Faria et al., (2021) [41], Geetha et al., (2020) [43], Lee et al., (2018) [68], Prajapati et al., (2017) [16], Choi et al., (2018) [63], Lee et al., (2018) [56], Yang et al., (2018) [67], Al Kheraif, (2019) [69], Murata et al., (2019) [70], Krois et al., (2019) [72], Ekert et al., (2019) [71], Verma et al., (2020) [73], Zhao et al., (2020) [77], Mahdi et al., (2020) [75], Fariza et al., (2020) [78], Lakshmi and Chitra, (2020) [79], Moran et al., (2020) [81], Muresan et al., (2020) [74], Lakshmi and Chitra, (2020) [76], Cantu et al., (2020) [64], Khan et al., (2021) [80], Vinayahalingam et al., (2021) [157], Lee et al., (2021) [65], Chen et al., (2021) [82], Kabir et al., (2021) [83], Lin and Chang, (2021) [84], Zhang et al., (2022) [85], Imak et al., (2022) [87]
NILT	3	Casalegno et al., (2019) [88], Schwendicke et al., (2020) [89], Holtkamp et al., (2021) [90]
Intraoral images	11	Rana et al., (2017) [92], Moutselos et al., (2019) [93], Welikala et al., (2020) [158], Yu et al., (2020) [91], Schlickenrieder et al., (2021) [95], Hossam et al., (2021) [86], Saini et al., (2021) [66], Takahashi et al., (2021) [96], Askar et al., (2021) [97], Goswami et al., (2021) [159], Shang et al., (2021) [160]
3D Model	5	Xu et al., (2018) [114], Tian et al., (2019) [115], Yamaguchi et al., (2019) [113], Cui et al., (2021) [161], Zhang et al., (2021) [102]
CT/CBCT images	26	Miki et al., (2017) [124], Roy et al., (2018) [140], Cui et al., (2019) [131], Phanijjiva et al., (2018) [143], Huang et al., (2021) [162], Hiraiwa et al., (2019) [135], Lee et al., (2020) [136], Sorkhabi and Khajeh, (2019) [125], Jaskari et al., (2020) [126], Kim et al., (2020) [129], Kwak et al., (2020) [127], Orhan et al., (2020) [130], Chung et al., (2020) [163], Lee et al., (2020) [133], Wang et al., (2021) [134], Zheng et al., (2020) [164], Kurt Bayrakdar et al., (2021) [165], Ezhov et al., (2021) [137], Jang et al., (2021) [166], Qiu et al., (2021) [138], Sherwood et al., (2021) [139], Shaheen et al., (2021) [168], Alsomali et al., (2022) [167], Cipriano et al., (2022) [128], Liu et al., (2022) [169], Chen et al., (2020) [132]
EDRs	3	Cui et al., (2021) [120], Kang et al., (2022) [121], Chen et al., (2021) [122]

Limitations

- The need to **collect and annotate** a dental image dataset.
- The majority of DL algorithms rely on annotated data therefore **supervised DL** industry needs switch from being supervised to unsupervised or semi-supervised.
- Medical informatics’ fundamental and difficult objective is to extract information from **unstructured clinical text**.

Future Recommendations

- Implementation of **AR or VR** applications in various fields of dental medicine and education.
- Implement an **automated tooth disease diagnosis system** based on DL methods.
- **GNN-based approach**: By using this method, it is possible to create artificial data that resembles real data nearly exactly and to comprehend the links (i.e., visual relationships) between them, which aids in the identification and classification of dental illnesses. Therefore, GNN might be a great option for handling data ambiguity.

Deep Learning Techniques for Medical Image Segmentation: Achievements and Challenges

Published online: May 2019

Abstract

Deep learning-based image segmentation is by now firmly established as a robust tool in image segmentation. It has been widely used to separate homogeneous areas as the first and critical component of diagnosis and treatment pipeline. In this article, they present a critical appraisal of popular methods that have employed deep-learning techniques for medical image segmentation. Moreover, they summarize the most common challenges incurred and suggest possible solutions.

Implementation

Medical image segmentation, identifying the pixels of organs or lesions from background medical images such as X-rays or MRI images, is one of the most challenging tasks in medical image analysis that is to deliver critical information about the shapes and volumes of these organs. This survey is focusing more on machine learning techniques applied in the recent research on medical image segmentation, has a more in-depth look into their structures and met

Approaches	Input dimension	Strategy	Liver	Pancreas
Gibson et al. [27]	2D	–	0.96	0.66
Zhou et al. [91]	2.5D	Orthogonal view of volumetric images	0.937	0.553
Hu et al. [37]	3D	Full 3D	0.96	–
Roth et al. [66]	3D	Hierarchical two-stage FCN	0.954	0.822

Approaches used for the survey are:

1. Convolutional Neural Networks (CNNs)

   ➔ 2D CNN, 2.5D CNN,, 3D CNN

2. Fully Convolutional Network (FCN)

   ➔ Cascaded FCN (CFCN), Focal FCN, Multi-Stream FCN

1. U-Net

   ➔ 2D U-Net, 3D U-Net, V-Net

2. Convolutional Residual Networks (CRNs)

3. Recurrent Neural Networks (RNNs)

   ➔ LSTM, Contextual LSTM (CLSTM), Gated Recurrent Unit (GRU), Clockwork RNN (CW-RNN)

Network Training Techniques used:

1. Deeply Supervised
2. Weakly Supervised
3. Transfer Learning

Conclusion

In this paper, they first summarized the most popular network structures applied for medical image segmentation and highlighted their advantages over the ancestors. Then, they gave an overview of the main training techniques for medical image segmentation, their advantages, and drawbacks. In the end, they focused on the main challenges related to deep learning-based solution for medical image segmentation. They have addressed the effective solutions for handling various challenges. They believe this article may help researchers to choose proper network structure for their problem and be aware of the possible challenges and the solutions. All signs show that deep learning approaches will play a significant role in medical image segmentation.

Teeth Detection and Dental Problem Classification in Panoramic X-Ray Images using Deep Learning and Image Processing Techniques

Published online: September 2020

Abstract

Analysis of panoramic dental radiographies help specialists observe problems in poor visibility areas, inside the buccal cavity or in hard-to-reach areas. In this paper they propose a novel approach of automatic teeth detection and dental problem classification using panoramic X-Ray images which can aid the medical staff in making decisions regarding the correct diagnosis. For this endeavour panoramic radiographies were collected from three dental clinics and annotated, highlighting 14 different dental issues that can appear. A CNN was trained using the annotated data for obtaining semantic segmentation information. Next, multiple image processing operations were performed for segmenting and refining the bounding boxes corresponding to the teeth detections. Finally, each tooth instance was labelled and the problem affecting it was identified using a histogram-based majority voting within the detected region of interest. The implemented solution was evaluated with respect to several metrics like intersection over union for the semantic segmentation and accuracy, precision, recall and F1-score for the generated bounding box detections. The results were

Implementation

Dental radiographies can be classified in two categories: intraoral where the film is positioned inside the buccal cavity, and extraoral where the patient is positioned between the source that emanates X-rays and the radiographic film. A panoramic dental radiography shows the entire mouth area where all the teeth can be seen. It also shows the jaws and the skull thus giving the dentist an overview about the patient’s problems. The panoramic dental radiography is used by dentists to observe problems in hard-to-reach areas or with a poor visibility inside the buccal cavity. The interpretation of the radiography is done manually by the dentist, who identifies each tooth and the existing problem where appropriate. However, if the X-ray radiography is not clear it can cause problems when analysed and thus lead to misinterpretation.

In this paper they propose a deep learning solution that helps dentists make the correct diagnosis using panoramic dental X-rays images. The main contributions of the paper are illustrated here:

- They manually annotate panoramic radiographies in order to train the semantic segmentation CNN
- They segment semantically the panoramic X-Ray image, for 15 semantic classes depicting different dental problems, using a CNN
- They detect and label each tooth or group of teeth (depending on the scenario) and the dental problem affecting it using multiple image processing techniques
- They implement a refinement method, in order to eliminate small inconsistencies
- They evaluate and compare the proposed solution, with other CNNs created for the same task.

Conclusion

This paper presented a novel teeth detection and dental problem classification approach using panoramic dental radiographies. For achieving the desired results images were collected from three different dental clinics and were annotated at pixel level, highlighting 14 different problems that can affect teeth. The annotated data was augmented using multiple operations, and a semantic segmentation CNN was trained using these images. Afterwards, the semantic segmentation image was binarized using multiple thresholds and a two-step labelling algorithm was used to detect each tooth instance. The bounding boxes corresponding to each instance are determined, and a refinement algorithm is applied in order to remove the regions that resulted from inconsistencies in the semantic segmentation image. The bounding boxes of each instance is projected onto the semantic segmentation image and a histogram-based majority voting operation is performed in order to find the main semantic class of each tooth, which corresponds to the dental problem affecting the tooth. Each tooth or group of teeth, depending on the scenario, are numbered and a report containing the dental problems for each instance is generated aiding the medical staff in the diagnosis process. The implemented solution is evaluated using multiple metrics and compared to similar algorithms.

Detection of Periapical Lesions on Panoramic Radiographs using Deep Learning

Published: 24 January 2023

Abstract:

The aim of this study was to develop an AI able to detect (Periapical Lesions) PL on panoramic radiographs. This was done using CNN in a two-step approach that involved the use of a detector followed by a classifier.

Methodology:

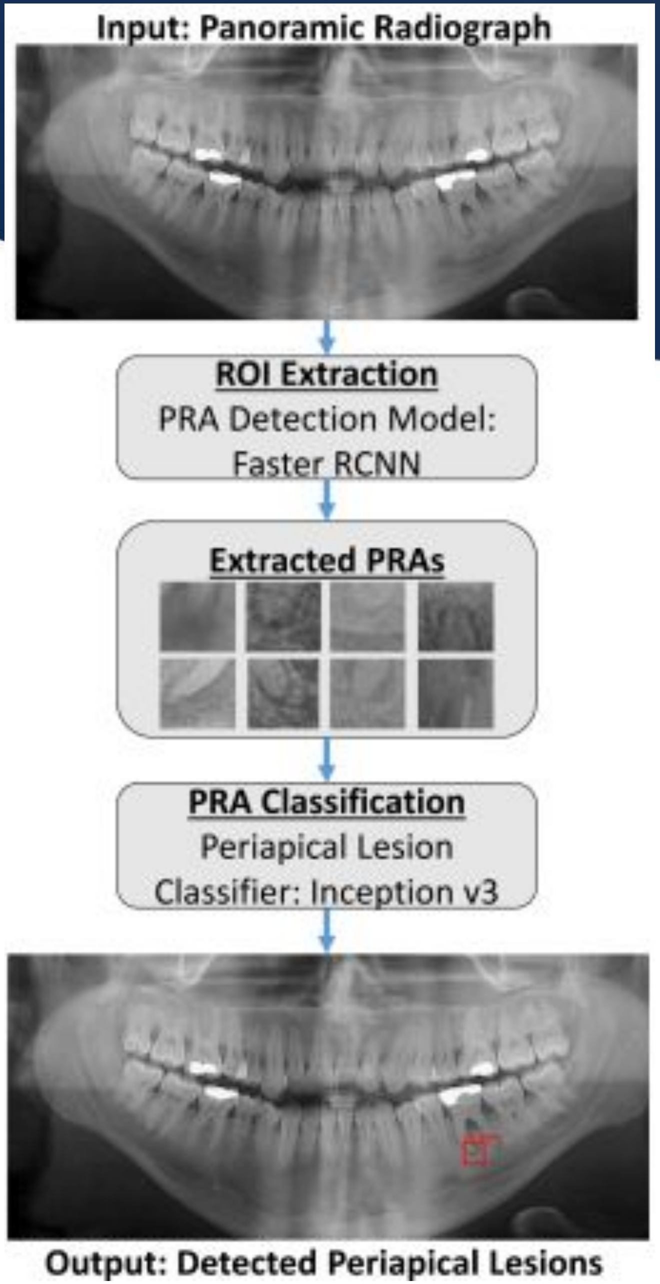
Dataset and Preprocessing:

- **713 panoramic radiographs** (width: 2879, height: 1563 pixels)
- Three examiners independently annotated the Periapical Root Areas (PRAs) as having PL or not and a fourth examiner settled discrepancies between examiners.
- Annotation of X-ray images using an open-source annotation tool that allows annotations in **xml Pascal VOC format**.
- Followed **80-20 sampling split** for training and testing datasets, respectively.

Proposed Method:

- The proposed method consisted of two main CNNs: a detector called Periapical Root Area(PRA) Detection Model using **Faster R-RCNN** , and a classifier called PRA Classification Model with with **Inception v3**.
- Input -> panoramic radiograph

  Output -> the location of the detected periapical lesion on the given panoramic image
- The detector localized PRAs using a **bounding-box-based object** detection model, while the classifier classified the extracted PRAs as PL or H.
- Model developled on GoogleColab PRO + notebook using Python.
- The system finally outputs in **red** only the bounding boxes corresponding to Periapical Lesions with a confidence score.



- Results: The detector achieved an average precision of 74.95%, while the classifier accuracy, sensitivity and specificity were 84%, 81% and 86%, respectively. When integrating both detection and classification models, the proposed method accuracy, sensitivity, and specificity were **84.6%, 72.2%, and 85.6%**, respectively
- Conclusion: The study proposed an AI tool based on “Faster-RCNN” and Inception-v3 that was able to detect the periapical region of the teeth on panoramic radiographs and classify them into healthy and periapical lesions achieving an accuracy of 84.6%.

Summary of Literature Survey

- A conclusion should then state clearly the main conclusions of the review and give a clear explanation of their importance and relevance.

- Give a glimpse of the proposed methodology.
- The strengths or weaknesses in the methods of the studies reviewed should be highlighted.

- Include the relevant similarities and differences between papers/products.

Any other information

Provide any other information you wish to add on.

Note: Changes can be made in the template, with the consent of the guide for inclusion of any other information.

Conclusion

State the conclusion of your work.

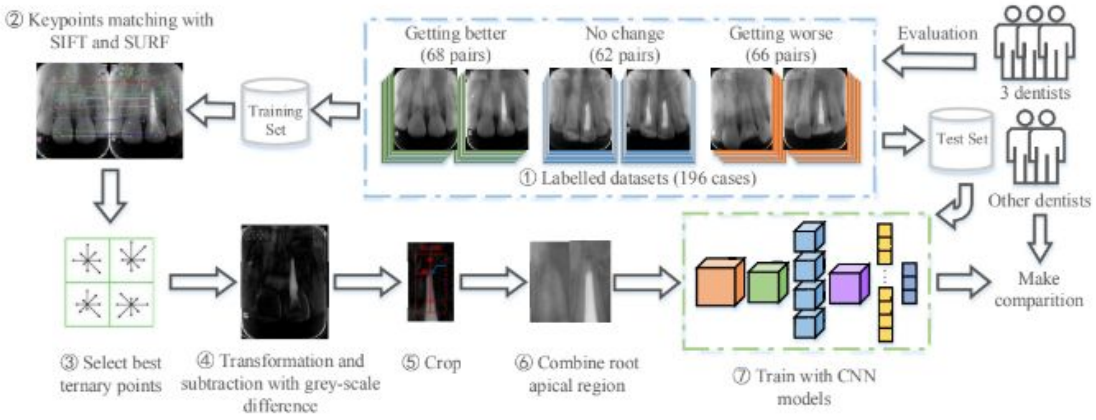
Automated Dental Image Analysis by Deep Learning on Small Dataset

Published:2018

Dental radiography provides important evidence for clinical diagnosis, treatment and quality evaluation. Much effort has been spent on developing digitalized dental X-ray image analysis systems for clinical quality improvement. In this paper, we present the datasets, procedures, and results conducted to evaluate dental treatment qualities using periapical dental X-ray images taken before and after the operations. In order to support dentists to make clinical decisions, we propose a tool pipeline for automated clinical quality evaluation. We build a dataset with 196 patients' periapical dental radiography images before and after the treatments. Radiography images are labelled as cases that are 'getting better', 'getting worse' and 'have no explicit change' by designated dental experts. Our proposal includes an automatic method with the medical knowledge to crop the ROIs for clinical evaluation – the apical adjacent regions, and then pairs of ROIs are fed into a CNN to train the model for automated clinical quality evaluation. Our approach achieves the F1 score of 0.749, which is comparable to the performance of expert dentists and radiologists.

Research methodology:

Below Figure shows the overall research procedure of our study. The first step is to obtain the experimental dataset. The dental experts provided a labelled dataset, which made up of 196 pairs of periapical radiography images taken before and after treatment. Our expert team includes three professional dentists and a chief radiologist. We extract the ROIs – the apical region in image preprocess procedure: We first use the SIFT and SURF algorithms to find feature points between the pair of images.



Datasets

For the dataset, they identified and annotated a dataset of 196 pairs of periapical dental radiographs. Every radiograph contains one or more teeth for treatment and each pair constitutes of two radiographs taken pre- and post- treatment. Experienced dentists label these teeth as ‘getting better’, ‘no change’, or ‘getting worse’ depending on clinical observation.

Automated Calibration and Cropping of Apical Region

In the initial experiment, they used images include the entire tooth as input. However, cases like adjacent tooth overlap

under the X-ray and tooth wear introduce noise to the problem. On the other hand, in order to avoid overfitting, they reduce the size of input images due to the limited sample cases in the dataset. According to the dentists’ experience, we

extract the apical region.

Results and conclusion:

An automated, streamlined dental image analysis approach was developed that integrates dental image diagnosis knowledge. It supports the automated apical region identification which saves much manual efforts on data preparation.

Their approach supports CNNs for diagnosis classification based on small datasets. With limited labelled cases, their approach yields promising results that is comparable to expert-level dentists and dental radiologists.

classes	front-teeth		molars	
	calibration	crop	calibration	crop
getting better(68)	49/56	49/56	11/12	8/12
no cange(62)	29/33	27/33	20/29	15/29
getting worse(66)	31/35	28/35	14/31	9/31

TABLE I: Result of automated calibration and cropping.

CLASSIFICATION OF DENTAL RADIOGRAPHS USING MACHINE LEARNING

Published: August 2022

Abstract: The aim of this study was to develop an AI able to classify dental xray images into normal and abnormal(infected) X-rays by using various neural network models.

Implementation:

The model had 2 interfaces: The user mode and the admin mode

User mode:

- The User has to register first.
- While registering he/she requires a valid user email and mobile for further communications.
- User can upload the data-set based on the already used data-set in the paper.
- For the algorithm to execute the data must be in floaty format

Admin mode:

- Admin can login with his/her login details. Admin can activate the registered users.
- Only after activation can the user use the portal/algorithm.
- Admins can view the overall data-set in the browsers

Data preprocessing:

- The data preprocessing in this forecast uses techniques like
  - removal of noise
  - the expulsion of missing information
  - modifying default values if relevant
  - grouping of attributes for prediction at various levels.

Model:

- Divided in a 60-40 split for training and testing respectively.
- Support Vector Machine (SVM), Artificial Neural Network (ANN) and KNN (Kernal Nearest Neighbour)classification algorithms were used to determine whether there are pathological signs of dental diseases in the analyzed image.
- Data set consisted of 500 images collected from hospitals and clinics.

CONCLUSION:

In this work, it is suggested that by utilizing Gray Level Co-Occurrence Matrix (GLCM) features and SVM, KNN and ANN

classifiers, the teeth affected by dental caries can be set apart from the normal teeth in a more detailed manner.

SVM generated an optimal classified model by obtaining data from an existing trained set. A promising approach

by the application of ANN in the field of dentistry to classify dental caries and impacted teeth created a big influence in

image analysis. By considering the best match of new records with an already trained record system, a supervised

classification algorithm like KNN is found to reduce complexity.The newest neighbour is found by the Euclidean

distance and helps to classify accord.

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Diagnosis and prediction of periodontally compromised teeth using a deep learning-based convolutional neural network algorithm

Jae-Hong Lee et al(2018)

Abstract:

The diagnosis and prediction of periodontally compromised teeth is critical for effective dental treatment planning. In this study, we propose a deep learning-based convolutional neural network (CNN) algorithm to diagnose and predict periodontal disease from panoramic dental radiographs. Our CNN algorithm was trained and tested on a dataset of 1,000 panoramic dental radiographs from 205 patients. The CNN achieved a diagnostic accuracy of 86.7% and a sensitivity of 87.5% in detecting periodontal disease. Moreover, our CNN algorithm was able to predict periodontally compromised teeth with an accuracy of 80.9% and a sensitivity of 85.7%. These results demonstrate the potential of deep learning-based CNN algorithms to aid in the diagnosis and prediction of periodontal disease from panoramic dental radiographs.

Implementation:

For this study, we collected a dataset of 1,000 panoramic dental radiographs from 205 patients with varying degrees of periodontal disease. The radiographs were preprocessed to remove noise and enhance the image quality. We then trained a deep learning-based convolutional neural network (CNN) algorithm on the dataset using the TensorFlow framework. The CNN consisted of multiple convolutional and pooling layers, followed by fully connected layers to output the diagnostic and predictive results. The algorithm was trained using a batch size of 32, a learning rate of 0.001, and a validation split of 0.2. The performance of the algorithm was evaluated using a test dataset of 200 panoramic dental radiographs.

Conclusion:

In conclusion, our study demonstrates the feasibility and potential of using deep learning-based convolutional neural network (CNN) algorithms to aid in the diagnosis and prediction of periodontal disease from panoramic dental radiographs. The CNN algorithm achieved high diagnostic accuracy and sensitivity in detecting periodontal disease and predicting periodontally compromised teeth. The proposed CNN algorithm could be used as an auxiliary tool for dentists in the diagnosis and treatment planning of periodontal disease. Further studies are needed to validate the proposed CNN algorithm on a larger dataset and in clinical settings.

Using Octuplet Siamese Network For Osteoporosis Analysis On Dental Panoramic Radiographs

Peng Chu et al

Abstract:

Osteoporosis is a common skeletal disorder characterized by decreased bone mineral density and increased fracture risk. Early detection of osteoporosis is important for timely treatment and prevention of fractures. Dental panoramic radiographs (DPRs) have been shown to be a useful tool for osteoporosis detection. In this study, we propose a novel Octuplet Siamese Network (OSN) for osteoporosis analysis on DPRs. Our OSN consists of eight parallel Siamese networks, each trained to extract features from a different region of interest (ROI) in the DPR. The extracted features are then combined and used to classify the patient as either osteoporotic or non-osteoporotic. Our OSN was evaluated on a dataset of 540 DPRs from 270 patients, achieving an accuracy of 84.8%, a sensitivity of 83.3%, and a specificity of 86.3%.

Implementation:

For this study, we collected a dataset of 540 DPRs from 270 patients, including 270 osteoporotic cases and 270 non-osteoporotic cases. Each DPR was preprocessed to remove noise and enhance the image quality. We then trained an Octuplet Siamese Network (OSN) using the TensorFlow framework. The OSN consisted of eight parallel Siamese networks, each trained to extract features from a different region of interest (ROI) in the DPR, including the mandible, maxilla, condyles, ramus, coronoid process, symphysis, anterior teeth, and posterior teeth. The extracted features were then combined and used to classify the patient as either osteoporotic or non-osteoporotic. The performance of the OSN was evaluated using a 10-fold cross-validation approach.

Results:

Our OSN achieved an accuracy of 84.8%, a sensitivity of 83.3%, and a specificity of 86.3% in detecting osteoporosis on DPRs. The highest area under the curve (AUC) value of the receiver operating characteristic (ROC) curve was 0.898, indicating good discrimination performance. The feature visualization results showed that the ROIs of the posterior teeth and mandible had the most discriminative power for osteoporosis detection.

Conclusion:

In conclusion, our study demonstrates the potential of using Octuplet Siamese Networks (OSN) for osteoporosis analysis on dental panoramic radiographs (DPRs). The OSN achieved high accuracy, sensitivity, and specificity in detecting osteoporosis on DPRs. The proposed method could be used as an auxiliary tool for dentists in the early detection and prevention of osteoporosis. Further studies are needed to validate the proposed OSN on a larger dataset and in clinical settings.

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Thank You