Literature Review

Paper-1

Title of the paper	Abdullah S. AL-Malaise AL-Ghamdi, Mahmoud Ragab, Saad Abdulla AlGhamdi, Amer H. Asseri, Romany F. Mansour, Deepika Koundal ”Detection of Dental Diseases through X-Ray Images Using Neural Search Architecture Network” Proceedings of the Fifth International Conference on Communication and Electronics Systems (ICCES 2020)
Area of Work	The paper explores the use of deep learning, particularly convolutional neural networks (CNNs), to enhance the diagnostic accuracy of dental diseases by analysing X-ray images.
Dataset	The dataset, from 116 patients at Noor Medical Imaging Centre, Qom, Iran, includes various dental conditions, from healthy to edentulous. Data augmentation increased the images from 83 to 245. The classification focused on three classes: cavity, filling, and implant.
Methodology/Strategy	Data augmentation techniques like scaling, rotation, translation, Gaussian blur, and noise enhanced dataset diversity. Preprocessing scaled images and encoded labels numerically, leading to a multi-output model using NAS Net with max-pooling layers, dropout layers, and activation functions.
Algorithm	The primary algorithm used is a NAS Net-based CNN.
Results/Accuracy	The proposed model achieved an accuracy greater than 96%.
Advantages	The model demonstrated high accuracy in classifying dental conditions by utilizing advanced deep learning techniques.
Limitations	The dataset was specific to a particular demographic, which might not represent broader populations.
Future Proposal	The authors suggest expanding the dataset with more diverse samples and incorporating additional dental conditions to further refine the model's accuracy and applicability.

Paper-2

Title of the paper	Michael G. Endres,Florian Hillen,Marios Salloumis,Ahmad R. Sedaghat ,Stefan M. Niehues,Olivia Quatela,Henning Hanken "Development of a Deep Learning Algorithm for Periapical Disease Detection in Dental Radiographs" Laboratory for Innovation Science, Harvard University, 175 N. Harvard Street, Suite 1350, Boston, MA 02134, USA(2021)
Area of Work	The paper falls under the intersection of medical imaging, artificial intelligence (AI), and dental radiography.
Dataset	The dataset consists of 2,902 de-identified panoramic radiographic images from the outpatient clinic at the Department of Oral and Maxillofacial Surgery, Charité, Berlin.
Methodology/Strategy	The methodology involved training a deep learning model on a curated dataset of labelled panoramic radiographs, with ground truth established by an experienced OMF surgeon, and comparing the model's performance with that of 24 OMF surgeons.
Algorithm	The deep learning model in this study is based on convolutional neural networks (CNNs), with the U-Net architecture referenced as a significant contribution to biomedical image segmentation, suggesting that a similar architecture might have been employed in this study.
Results/Accuracy	The deep learning model achieved a mean accuracy of 67%.
Advantages	The model's performance in detecting periapical radiolucency was on par with experienced OMF surgeons.AI models provide consistent performance, whereas human performance may vary.
Limitations	The model's performance was evaluated on a specific dataset, and its generalizability to data from other sites or different imaging practices remains to be demonstrated.
Future Proposal	Collecting training data from multiple sites to enhance the model's robustness across different imaging practices and patient populations. Expanding the dataset size by 10- to 100-fold could significantly improve the model's performance.

Paper-3

Title of the paper	Hu Chen,Hong Li7,Yijiao Zhao,Jianjiang Zha,Yong Wang "Dental disease detection on periapical radiographs based on deep convolutional neural networks" International Journal of Computer Assisted Radiology and Surgery (2021)
Area of Work	The paper falls under the intersection of medical imaging, artificial intelligence (AI), and dental radiography.
Dataset	In total, 2900 digital dental periapical radiographs were collected. Classification based on Decay-mild, Decay-moderate, Decay-severe, Periapi-mild, Periapi-moderate, Periapi-severe, Periodo-mild, Periodo-moderate, Periodo-severe
Methodology/Strategy	The Faster R-CNN model was trained and validated using several strategies. Training with all annotated images (baseline).Training by ignoring severity levels. Training separate models for each disease type. Training separate models for each severity level
Algorithm	The study used the Faster R-CNN algorithm, trained with TensorFlow and fine-tuned with a pre-trained COCO model, using specific anchor scales, iterations, and learning rates.
Results/Accuracy	The deep learning model achieved a best accuracy of 71.59%.
Advantages	The use of deep learning can significantly automate the process of diagnosing dental conditions from X-ray images. Efficiency: Deep neural networks can process and classify images quickly, making real-time or near-real-time diagnosis possible.
Limitations	The model's performance was evaluated on a specific dataset, and its generalizability to data from other sites or different imaging practices remains to be demonstrated.
Future Proposal	Collecting training data from multiple sites to enhance the model's robustness across different imaging practices and patient populations. Expanding the dataset size by 10- to 100-fold could significantly improve the model's performance.

The reviewed papers highlight the effectiveness of various deep learning architectures in diagnosing dental conditions through X-ray images, with each study showcasing specific strengths and limitations.

Paper 1, "Detection of Dental Diseases through X-Ray Images Using Neural Search Architecture Network," utilized NAS Net, achieving over 96% accuracy in classifying conditions like cavities and implants, though it was limited by a small, demographically specific dataset.

Paper 2, "Development of a Deep Learning Algorithm for Periapical Disease Detection in Dental Radiographs," employed a U-Net-like CNN, achieving a mean PPV of 0.67 and TPR of 0.51, matching the performance of experienced OMF surgeons but requiring a larger dataset for better generalization.

Paper 3, "Deep Learning Algorithms for Detecting Dental Diseases in Periapical Radiographs Using Faster R-CNN," used the Faster R-CNN architecture, achieving best accuracies of 71.59% IoU, 61.93% Precision, 61.29% Recall, and 46.83% AP, demonstrating the potential of object detection models in dental diagnostics. The papers collectively underscore the need for diverse, expansive datasets and further exploration of advanced neural network architectures to enhance diagnostic accuracy and generalizability across various clinical settings

Proposed Model

Deep Learning-Based Classification of Dental Pathologies from Radiographic Images

Building on the findings from the reviewed literature, the proposed project aims to develop an advanced deep learning model using the **NAS Net architecture** for predicting dental diseases. The model will be trained on a comprehensive dataset of over 8000 radiographic images, each annotated for four distinct dental conditions: **cavity, implant, filling, and impacted tooth**.

The cavity class will identify areas of decay in the tooth structure, while the implant class will detect the presence of dental implants. The filling class will classify regions where dental restorations have been applied, and the impacted tooth class will identify teeth that have not erupted properly or are misaligned.

The primary goal is to leverage the robust feature extraction capabilities of NAS Net to achieve high accuracy and generalizability across diverse patient demographics. The project will include rigorous data augmentation and preprocessing steps to enhance model robustness and mitigate biases. Additionally, the implementation will focus on optimizing the network architecture for efficient training and inference, making it suitable for practical clinical deployment. The proposed model aims to provide reliable, automated diagnostic support, potentially surpassing traditional methods and assisting dental professionals in making more accurate and timely diagnoses.

Motivation for NAS Net

1.Architecture Optimization: NAS Net is designed with Neural Architecture Search (NAS) techniques that optimize the network architecture automatically, leading to highly efficient and effective models.

2.Feature Extraction: NAS Net's architecture provides robust feature extraction capabilities, which are crucial for accurately identifying and classifying complex dental conditions from radiographic images.

3.High Accuracy: NAS Net has demonstrated superior performance in various applications, including image classification and object detection, making it well-suited for achieving high accuracy in diagnosing dental diseases.

4. Scalability: The model can handle large datasets and complex image features, which is essential given the comprehensive dataset of over 8000 radiographic images.

Dataset

The dataset comprises 8,030 entries, each corresponding to a dental radiographic image with detailed annotations. These annotations are crucial for identifying and classifying dental conditions, primarily focusing on four categories: cavity, implant, filling, and impacted tooth.

Width: The width of the image in pixels, indicating the resolution and aspect ratio.

Height: The height of the image in pixels, providing additional information about the image's dimensions.

Class: The category of the dental condition present in the image. The main classes are:

Cavity: Identifies areas of tooth decay.

Implant: Detects the presence of dental implants.

Fillings: Recognizes areas where dental restorations have been applied.

Impacted Tooth: Identifies teeth that have not erupted properly or are misaligned.

Preprocesses status: The dataset is well per processed an did not found any unwanted or noisy contents in it

The dataset is carefully annotated to include information about the specific conditions present in each image. This includes:

Class Identifiers: Each condition is marked with a specific class identifier, allowing for the distinction between different types of dental issues.

Bounding Boxes: The bounding boxes are used to pinpoint the exact location of the condition within the radiograph. This is crucial for training object detection models, which require precise localization information.

Comprehensive Annotations: The dataset provides detailed annotations for each image, covering a wide range of dental conditions. This richness in data makes it an excellent resource for training and evaluating machine learning models.

High-Resolution Images: The images are of high quality, with sufficient resolution to discern fine details, essential for accurate diagnosis and analysis.

Diverse Condition Coverage: By including various dental conditions, the dataset ensures that models trained on it can generalize well to real-world scenarios.