Methodology Issue

AI-Enabled Dental Imaging for Oral Disease Detection

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Abstract:

This study aims to enhance the accuracy and efficiency of dental diagnostics using deep learning models to automatically detect and classify oral disease and dental structures on panoramic radiographs. By employing a quantitative research methodology, the study evaluates key performance metrics. The model's ability to accurately detect dental anomalies, such as caries, periodontal conditions, restorations, and implants, shows significant promise for real-time clinical applications (Arsiwala-Scheppach et al., 2023). In parallel, the study explores the broader potential of Artificial Intelligence in dental imaging, addressing current limitations such as the adaptability of models trained on narrow datasets. It emphasises the importance of expanding datasets to capture a wider range of patient demographics and imaging modalities and highlights the need to validate Artificial Intelligence models in real-world clinical settings (Putra et al., 2022). Together, this research underscores the transformative role of Artificial Intelligence in modernising dental diagnostics, moving from traditional methods to advanced Artificial Intelligence enhanced techniques (Patil et al., 2022).

Key words: Dental imaging, Dental Radiography, Artificial Intelligence (AI), YOLO models, Preventive Diagnostics, Object Detection

Research questions:

Primary Research Question:

What is the efficacy of Artificial Intelligence (AI) enabled dental imaging techniques in the assessment of multiple oral diseases?

Secondary Research Questions:

- To what extent can AI algorithms enhance the precision of oral disease diagnosis when applied to dental X-ray images?
- How does AI-assisted oral disease assessment compare to traditional diagnostic methods in terms of speed and accuracy?

Research Objectives

I am particularly interested in this topic because of the growing potential for AI to revolutionise healthcare, especially in the field of medical imaging. Dental diagnostics, in particular, is an area where AI-driven solutions can have a significant impact by improving the accuracy and speed of diagnosis, which can ultimately lead to better patient outcomes (Carrillo-Perez et al., 2022). Panoramic radiographs often present a challenge due to the dense and complex nature of dental structures. Developing models to automate the detection of anomalies can reduce the workload for clinicians and enhance diagnostic consistency (Patil et al., 2022).

Furthermore, my background in both health informatics and dentistry makes this research a natural progression of my interest in applying advanced computational techniques to solve practical healthcare problems. I am motivated by the possibility of making dental diagnostics more accessible, efficient, and scalable, particularly in settings where resources and specialists are limited. This project allows me to combine my technical skills with my passion for healthcare innovation, pushing the limits of what AI can achieve in clinical settings.

Research Design/ Methodologies

The primary research design that I chose for this study is a quantitative approach. I selected this method because it allows for a systematic evaluation of the performance of various object detection models. Quantitative research is ideal for this project, as it focuses on using numerical data to assess accuracy, computational efficiency, and model performance through objective metrics like Mean Average Precision (mAP), Precision, Recall, and Intersection over Union (IoU).

Why this Methodology was Chosen: Quantitative research is well suited to validate the effectiveness of various model configurations and preprocessing techniques in detecting and localising dental structures such as restorations, caries, and implants in panoramic radiographs. By leveraging this method, I can generate statistically valid data that support objective, reproducible conclusions about the model's performance in real-world diagnostic environments. This methodology also enables a data-driven approach to model optimisation, allowing me to compare different augmentation strategies, model setups, and hyperparameter tuning efforts.

The dataset comprises panoramic dental radiographs sourced from public repositories. Radiographs cover a wide range of dental conditions, including caries, missing teeth, restorations, implants, and many other dental conditions. The data set includes variations in image quality and dental conditions to ensure that the model can be generalised to different real-world scenarios. Data annotation was performed by expert dentists to ensure high-quality bounding box labelling using Roboflow software (Welikala et al., 2020). Data were collected once, but data enhancement techniques such as rotation, flipping, and contrast adjustments were used to expand the variability in the data set and avoid overfitting during model training. The variability within the dataset, achieved through the inclusion of radiographs with differing image quality, dental anomalies, and imaging conditions, supports the generalisability of the model. By incorporating the enhancement techniques, the dataset further simulates real-world scenarios. This variability enhances the model's ability to generalise to unseen data, thereby increasing its clinical applicability.

We plan to conduct a comparison of various models, including YOLO NAS, YOLO v9, YOLO v8 and YOLO v5, to determine which model performs best (Rashidi Ranjbar & Zamanifar, 2024). The comparative analysis across YOLO versions aims to identify the optimal balance of speed, accuracy, and generalisability for dental anomaly detection. The selection of YOLOv5, YOLOv8, YOLOv9and YOLO-NAS for this study on AI-driven dental imaging was based on their state-of-the-art performance in object detection tasks, especially in the medical and dental imaging domains. These models offer unique capabilities in terms of speed, accuracy, and adaptability, making them highly suitable for addressing the specific challenges of oral disease detection in clinical settings. The decision was further supported by comparative studies and benchmarks. YOLOv5 stands out for its balance of speed and accuracy, making it a popular choice for a wide range of object detection tasks. Building on this foundation, YOLOv8 and YOLOv9 offer enhanced computational efficiency and improved accuracy, thanks to advancements in their architectural design. Additionally, YOLO NAS leverages Neural Architecture Search (NAS) to optimise model design, ensuring tailored performance for specific datasets.

To identify the most effective model for our task, we will conduct a comprehensive comparison of various deep learning models. PyTorch has been selected as the primary framework due to its flexibility and compatibility with multiple models, enabling seamless architecture optimisation. Efficient batch processing is achieved through parallelised data loaders, while augmentation techniques are employed to enhance dataset variability and improve model robustness. Data augmentation plays a key role in improving model resilience by simulating varied imaging conditions, reducing the likelihood of overfitting. PyTorch's advanced architecture customisation and integration with state-of-the-art models streamline the training process, enabling efficient experimentation.

The evaluation focuses on critical metrics such as speed, accuracy, and real-time performance, which are paramount for dental diagnostics. TensorBoard will be utilised to monitor training progress, providing real-time visualisation of metrics like accuracy, mean Average Precision (mAP), and Intersection over Union (IoU). This helps identify and address trends of overfitting or underfitting early in the training process. To ensure reliability, we are incorporating early stopping mechanisms to mitigate overfitting risks and repeating the training process with different random seeds to validate consistency. Cross-validation will further enhance model generalisability by testing performance across diverse data subsets, ensuring robust outcomes on unseen data. Training results will be systematically logged in TensorBoard for easy tracking and exported as CSV files for in-depth analysis and reproducibility. This comprehensive approach ensures the identification of the best-performing model tailored to our specific requirements.

A key limitation is the reliance on GPU resources. While the model performs well, its efficiency could be further improved with more powerful hardware (e.g., larger GPUs), especially for larger datasets. Additionally, the current dataset is limited to publicly available radiographs, which may not fully represent the diverse demographic and imaging conditions encountered in clinical settings. Additionally, while data augmentation increases variability, it cannot entirely substitute for genuine demographic and equipment diversity. Future studies should aim to include more heterogeneous datasets to address these constraints.

Words of wisdom/ hints

For researchers following a similar path, I recommend ensuring that your data are adequately annotated, as high-quality annotations are crucial for model accuracy. Continuously evaluate model performance after each training epoch and adjust your approach based on the validation results to avoid overfitting and underperformance.

Conclusion

At this stage, I am still in the experimental phase, and while the quantitative methodology has provided a solid framework for analysing the performance of different models in detecting dental conditions, I remain hopeful that the approach will prove effective. Based on the findings in the existing literature, I anticipate that this method will lead to meaningful and robust solutions for real-world applications in dental diagnostics. However, ongoing experimentation and validation are necessary to confirm these results.

Short Bio

I am an internationally trained dentist from India with a Master's degree in Health Informatics, and I am currently pursuing a Research Master's in Computer and Information Sciences at Auckland University of Technology (AUT). My research focuses on dental informatics, health informatics, digital health, and medical image processing. I also work as a research assistant on several digital health projects at AUT. My passion is to advance both dental and medical informatics to improve healthcare delivery, and I am keen to apply my expertise to drive impactful healthcare projects.

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