ADVANCING DENTAL RADIOGRAPH CLASSIFICATION USING DEEP LEARNING: A STUDY ON RESNET AND EFFICIENTNET ARCHITECTURES

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ABSTRACT

Dental radiography is critical in modern dentistry, especially in implantology, where accurate diagnosis and effective planning are essential. This study leverages advanced deep learning models to classify dental radiographs, aiming to improve diagnostic precision and streamline clinical workflows. A balanced dataset of 25,000 images, divided into five distinct classes, was prepared using undersampling and data augmentation to ensure robust model training and generalization.

The performance of two leading deep learning architectures, ResNet[1] and EfficientNet[2], was evaluated. These models achieved test accuracies of 99.04% and 99.52%, respectively, demonstrating their high effectiveness in dental radiograph classification. The models also addressed challenges such as complex anatomical structures and imaging artifacts like noise and distortions, showcasing their robustness in practical applications.

This research highlights the potential of AI-driven methodologies to enhance automated diagnostic systems in dentistry. The findings provide a foundation for developing reliable and accessible tools tailored to clinical needs, ultimately advancing patient care. Future work will focus on extending the scalability of these models across diverse clinical settings and incorporating additional imaging modalities to broaden their applicability.

1. INTRODUCTION

Dental radiography plays a pivotal role in modern dentistry, especially in implantology, where accurate diagnosis and treatment planning are fundamental. High-resolution dental images, such as periapical, panoramic, and cone-beam computed tomography (CBCT) scans, are indispensable for assessing anatomical structures, identifying pathologies, and planning procedures like dental implants. However, the manual interpretation of these images can be time-consuming, prone to human error, and reliant on the expertise of clinicians.

Recent advances in artificial intelligence (AI) and deep learning have demonstrated remarkable potential in medical imaging tasks, including classification, segmentation, and anomaly detection. Deep learning models, particularly convolutional neural networks (CNNs), have revolutionized image analysis by automating complex tasks and achieving high accuracy across various applications. In dental radiography, these models can enhance diagnostic precision, streamline workflows, and support clinical decision-making.

This study focuses on the classification of dental radiographs using advanced deep learning architectures, namely ResNet and EfficientNet. A carefully curated and balanced dataset of 25,000 images, distributed across five classes, was utilized to train and evaluate these models. Techniques such as data augmentation and undersampling were employed to address class imbalance and improve model robustness. The models achieved impressive test accuracies of 99.04 and 99.52, respectively, demonstrating their effectiveness in classifying dental radiographs.

Moreover, the research addresses key challenges in dental image analysis, including the complexity of anatomical structures and the presence of imaging artifacts. By leveraging state-of-the-art AI techniques, this work aims to contribute to the growing field of automated dental diagnostics, offering insights into the practical applications of deep learning in dentistry. Ultimately, it seeks to pave the way for more accurate, reliable, and accessible diagnostic tools that can improve clinical outcomes and patient care.

2. RELATED WORKS

Deep learning has made significant progress in dental implantology, especially in tasks like image analysis, segmentation, and treatment planning. Many researchers have worked on improving these areas using advanced AI models.

For example, Al-Asali el al. [3] developed a DL-based approach for 3D bone segmentation and prediction of missing tooth region for dental implant planning. They utilized U-Net models to segment bone in regions where teeth are missing in cone-beam computerized tomography (CBCT) scans and predict the positions of implants. The proposed models were applied to a CBCT dataset of Taibah University Dental Hospital (TUDH) patients between 2018 and 2023. They were evaluated using different performance metrics and validated by a domain expert. The experimental results demonstrated outstanding performance in terms of dice, precision, and recall for bone segmentation (0.93, 0.94, and 0.93, respectively) with a low volume error (0.01). The proposed models offer promising automated dental implant planning for dental implantologists.

In another study [4] Kurt et al. developed a DL approach for dental implant planning in cone-beam computed tomography images. The authors used a dataset of Seventy-five CBCT images. In these images, bone height and thickness in 508 regions where implants were required were measured by a human observer with manual assessment method. Also, canals/sinuses/fossae associated with alveolar bones and missing tooth regions were detected. The jaws were separated as mandible/maxilla and each jaw was grouped as anterior/premolar/molar teeth region. The data obtained from manual assessment and AI methods were compared using Bland–Altman analysis and Wilcoxon signed rank test. In the bone height measurements, there were no statistically significant differences between AI and manual measurements in the premolar region of mandible and the premolar and molar regions of the maxilla (p¿0.05). In the bone thickness measurements, there were statistically significant differences between AI and manual measurements in all regions of maxilla and mandible (p¡0.001). Also, the percentage of right detection was 72.2% for canals, 66.4% for sinuses/fossae and 95.3% for missing tooth regions.

For example, Park et al. (2022) and Bayrakdar et al. (2021) used U-Net and CNN models to identify missing teeth [3] and plan implants based on radiographic and CBCT data. Their methods showed high accuracy, especially in segmenting complex dental structures. Similarly, Moufti et al. (2023) and Al-Sarem et al. (2022) applied transfer learning and U-Net architectures to improve 3D imaging segmentation, achieving promising results.

However, challenges remain, such as handling noise in images, differences in dental anatomy, and artifacts caused by restorations, as noted by Schwendicke et al. (2019). Other studies, like Alsomali et al. (2022) and Kernen et al. (2016), explored combining AI with technologies like 3D printing to enhance implant planning accuracy and efficiency.

In addition, Kwak et al. and Jaskari et al. focused on AI in CBCT imaging to analyze important anatomical features like mandibular canals and bone structures. Their findings show that deep learning can help standardize and simplify implant planning, but more work is needed to create fully automated systems.

Some studies also concentrated on implant classification. Lee et al. (2020) and Santos et al. (2021) used CNNs and architectures like ResNet to classify implant types and brands, achieving high accuracy. However, these approaches often required large datasets and faced challenges related to generalization and real-world testing.

Recent advancements, like those by Nogueira-Reis et al. (2023) and Lahoud et al. (2022), demonstrated the strength of CNN-based models such as 3D U-Net in segmenting dental structures. These methods showed good results but still struggled with artifacts from CBCT images and the segmentation of implants and crowns.

3. METHODS

3.1. Dataset Description

In this study, we utilized the OII-DS dataset[5] , initially consisting of approximately 11,000 CT images of curved oral cavity surfaces. These images were collected at the School and Hospital of Stomatology, China Medical University, with ethical approval obtained under reference number 2022PS433K. After careful sorting, screening, and format harmonization, a final set of 3,834 images was selected. These images, in PNG format, were derived from postoperative CT scans of approximately 3,000 patients treated between 2011 and 2016.

The dataset is notable for its diversity and detailed annotations, including the following key attributes:

Implant brands:

The dataset includes implants from Nobel (Sweden)[6], ITI (Switzerland)[7], Osstem (Korea)[8], Astra (Sweden)[9], Bego (Germany)[10], Anthogyr (France)[11], Lifecore (USA)[12], Dentium (Korea)[13], and BLB (China)[14].

Implant dimensions:

Diameter: Ranging from 3.0 mm to 5.4 mm. Length: Ranging from 6 mm to 14 mm.

Implant positions: The dataset covers anterior teeth, premolars, and molars.

Implant applications: Single-tooth restorations, fixed bridges on implants, implant overdentures, and full fixed denture restorations.

CT machine specifications:

-Brand and type: KaVo, CBCT I-CAT.

-Radiation dose: 0.1 mSv.

-Scanning time: 26.9 seconds.

Imaging software:

The images were processed using Simplant, a widely used third-party software in dental imaging.

To ensure robust evaluation and generalizability of the classification models, the dataset was divided into training, validation, and testing subsets. This meticulous approach ensures that the models are trained and tested under consistent and reproducible conditions, enhancing their reliability in clinical applications.

To provide a better understanding of the database structure, an example is presented below, illustrating the type of image contained in each folder. This helps to better visualize the diversity of dental radiographs used in this study.

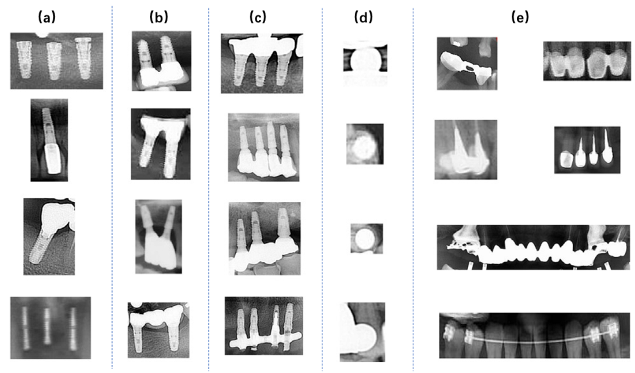

Fig. 1. Extraction and sampling from each folder of the dataset, providing a view of the images contained in the five categories: (a) single implant, (b) double implant, (c) compound, (d) steel ball, (e) compound.

3.2. Preprocessing Method

The preprocessing of the dataset was a crucial step to prepare the images for classification. First, all images were resized to a uniform resolution of **224x224 pixels** to ensure compatibility with deep learning models and reduce computational complexity. This resizing was performed using the PIL (Python Imaging Library). Additionally, all images were normalized by scaling the pixel values to the range $[0, 1]$, which ensures faster convergence during model training.

The images were then inspected to identify any potential anomalies such as incorrect formats or corrupt data. Finally, the preprocessed images were stored efficiently using the `NumPy` library, which allowed for faster loading during the model training phase.

3.3. Initial Dataset Imbalance

Before balancing, the dataset exhibited significant imbalance across the five classes:

- **single_implants**: 6616 images
- **double_implants**: 634 images
- **steel_ball**: 2641 images
- **compound**: 323 images
- **others**: 5026 images

This imbalance posed a challenge for model training, as it could lead to biased predictions favoring the overrepresented classes while neglecting the underrepresented ones. To address this issue, we applied the **Data Balancing Method** described below.

Data Balancing Method

To ensure a perfectly balanced dataset, we standardized the distribution of images across the five categories: *single_implants*, *others*, *double_implants*, *compound*, and *steel_ball*. Each category was normalized to contain exactly **5000 images** by combining two main techniques: **undersampling** and **data augmentation**.

- For classes with a surplus of images, **undersampling** was performed by randomly selecting **5000 images**.
- For underrepresented classes, **data augmentation** techniques were applied, including random *rotation*, *zooming*, *translation*, and *horizontal flipping*. These augmentations were implemented using the ***ImageDataGenerator*** library from Keras.

This step allowed us to generate new image instances from the existing data while preserving the diversity of visual patterns. As a result, the final dataset is perfectly balanced, comprising a total of **25,000 images** evenly distributed across the five classes. This balance ensures fair and unbiased learning for our classification model.

4. RESULTS

The performance of the models was evaluated through various metrics, including validation accuracy and loss curves, which provide insights into the learning behavior of the networks.

Validation Accuracy: The validation accuracy curve (Fig. 3) demonstrates the effectiveness of the models in classifying dental radiographs. Despite minor fluctuations, the accuracy consistently remained above 99.04%, with peaks nearing 99.52% around specific epochs. These results highlight the robustness of the models in addressing the complexity of dental imaging data, including intricate anatomical details and imaging artifacts. The occasional dips in accuracy, observed at epochs 5 and 13, may be attributed to the stochastic nature of mini-batch gradient descent and the inherent variability of the validation dataset.

Train vs Validation Loss: The training and validation loss curves (Fig. 2) exhibit a steady decline, with the training loss dropping significantly from an initial value of approximately 0.12 to below 0.01. The validation loss follows a similar trend but displays slight oscillations at certain epochs, reflecting the model's sensitivity to unseen data. The convergence of both curves toward low values suggests that the models effectively learned the underlying patterns in the dataset without substantial overfitting.

These results underline the effectiveness of ResNet and EfficientNet architectures in handling the challenges of dental radiography classification. The high validation accuracy, combined with the low and stable loss values, demonstrates the potential of these models to provide reliable and consistent performance in clinical applications. Further optimization, such as fine-tuning hyperparameters or employing advanced regularization techniques, may further enhance the stability and generalization of the models.

Loss graph

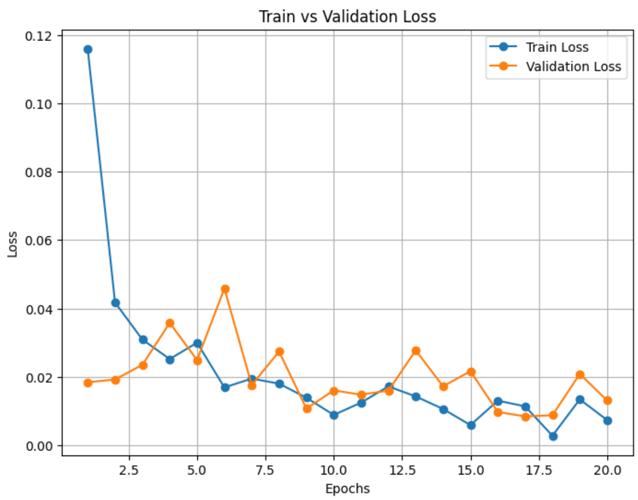

Fig. 2. Courbe de la perte pour l'entraînement et la validation.

Graph of precision

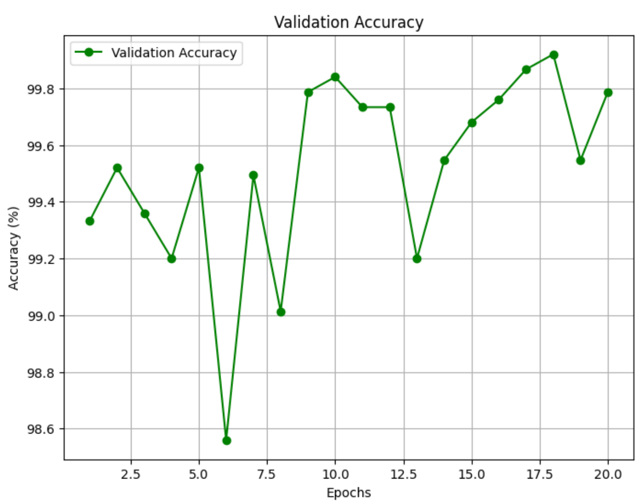

Fig. 3. Courbe de la précision pour l'entraînement et la validation.

5. DISCUSSION

The results achieved in this study, with test accuracies of 99.04% for ResNet and 99.52% for EfficientNet, confirm the efficiency of these deep learning architectures in classifying dental radiographs. These performances underscore the models' ability to address specific challenges inherent to dental data, such as the complexity of anatomical structures and imaging artifacts, including noise and distortions.

Compared to prior works employing models like U-Net for segmentation[3] or other CNN architectures for classification[15], our findings stand out due to their high precision and robustness. This success can be attributed to the meticulous preparation of the dataset, which involved advanced undersampling and data augmentation techniques. Previous studies, such as those by Schwendicke et al. (2019)[16], highlighted the challenges posed by imaging artifacts, a challenge that was mitigated in our study through the advanced capabilities of the tested models.

From a clinical perspective, these results present significant opportunities to enhance dental diagnostics. The models evaluated could serve as reliable tools for implant identification, reduce human errors, and optimize treatment planning workflows. Their robustness in processing complex images is particularly valuable for cases involving multiple restorations or anatomical anomalies.

However, certain limitations must be acknowledged. Firstly, the dataset used originates from a single source, which may limit the generalizability of the results. Validation using multicenter datasets is necessary. Secondly, while the models demonstrated resilience to artifacts, extremely noisy images or highly complex cases may still present challenges. Lastly, the high computational cost of training these models remains a barrier to their implementation in resource-limited clinical environments.

Future research could focus on the following directions:

Evaluating the models on datasets from multiple medical centers to validate their robustness and generalizability. Integrating additional imaging modalities, such as panoramic or CBCT images, to broaden their applicability. Leveraging emerging approaches, such as visual transformers or attention networks, to better capture complex details in radiographs. Developing real-time solutions that can be directly applied in dental clinics for faster, automated diagnostics. In conclusion, this study highlights the potential of ResNet and EfficientNet to transform the classification of dental radiographs. These findings pave the way for more reliable and accessible automated diagnostic systems, ultimately contributing to improved patient care.

6. CONCLUSION

This study highlights the significant impact of deep learning models in dental radiograph classification, particularly in the field of implantology. By leveraging advanced architectures such as ResNet and EfficientNet, we achieved exceptional results, with test accuracies of 99.04

The results confirm that artificial intelligence, particularly convolutional neural networks, can play a pivotal role in modernizing diagnostic practices in dental implantology. This research paves the way for automated and more accessible solutions, assisting in clinical decision-making with enhanced precision and reliability.

However, several avenues for further research remain to refine these systems. Challenges related to the diversity of clinical images, missing data management, and the integration of these models into real-world clinical environments require further investigation. Additionally, future steps will include assessing the impact of these systems on clinical practices and their large-scale adoption.

Thus, this work represents a significant contribution to the field of automated diagnostics, offering promising prospects for a future where artificial intelligence technologies are central to advances in dental implantology.

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