IDENTIFICATION OF DENTAL IMPLANTS USING DEEP LEARNING

Youssef Merzouk, Adam El Bakkali, Mohamed Dioua , Nizar Madani

International University of Rabat
College of Engineering & Architecture

ABSTRACT

Dental implantology requires precise planning and analysis to ensure successful outcomes. The advent of deep learning (DL) has revolutionized the medical field, offering automation, accuracy, and efficiency in tasks like diagnosis and treatment planning. This study explores the use of a fine-tuned ResNet50 model for the classification and analysis of dental radiographs related to implants. The dataset consisted of over 5,000 annotated radiographs categorized into five classes, preprocessed using resizing, normalization, and data augmentation techniques. The ResNet50 model, pre-trained on ImageNet, was fine-tuned by unfreezing the last 10 layers, achieving a test accuracy of 92.3% and a test loss of 0.28. The results highlight the effectiveness of transfer learning in handling medical imaging tasks, especially in domains with limited data availability. Future research could explore advanced architectures like Vision Transformers and the integration of 3D imaging data to further enhance performance.

Index Terms— Deep Learning, Dental Radiographs, Dental Implants, ResNet50, Transfer Learning.

1. INTRODUCTION

Artificial intelligence (AI) has revolutionized the medical field, with Deep Learning (DL) leading this transformation. Its ability to process large-scale data and deliver accurate results has positioned AI as an essential tool in modern medicine [1]. In dentistry, DL has opened new opportunities by automating complex tasks such as diagnosis, treatment planning, and prognosis, greatly improving precision, speed, and reliability in clinical decision-making [2].

Role of Dental Radiography Dental radiography is a critical tool in dental diagnosis and treatment planning. It provides detailed images of teeth, jaws, and surrounding structures, indispensable for evaluating oral health and planning interventions like implants. However, manual analysis of these images is time-consuming and prone to human error due to the complexity and variability of dental structures. DL addresses these challenges by automating radiograph analysis, offering insights that were previously unattainable through traditional methods [3].

Applications in Dental Implantology Among the various applications of DL in dentistry, dental implantology stands out as a domain requiring high precision. Dental implants (DI) demand meticulous evaluation of:

- Bone quality,
- Jaw structure,
- Spatial positioning.

Errors in planning or execution can lead to severe complications, including implant failure or damage to adjacent structures [4]. DL algorithms excel in this domain by integrating and analyzing diverse data sources, such as:

- Panoramic X-rays,
- 3D CBCT (Cone-beam computed tomography systems) scans.

Evolution of DL in Implantology The role of DL in dental implantology has evolved significantly. Initially focused on simple detection tasks, it now encompasses more complex processes such as:

- Predicting the optimal implant position,
- Analyzing implant stability,
- Classifying implant types.

Advancements in neural networks, particularly convolutional neural networks (CNNs) and transformer-based architectures, have enabled the extraction of fine-grained features from radiographs and the integration of contextual information. These models have demonstrated success in automating workflows, improving diagnostic accuracy, and enhancing clinical outcomes [4].

Objective of the Project This project aims to utilize DL for the classification and analysis of dental radiographs in implant-related care. By leveraging state-of-the-art models and datasets, the objective is to develop a robust system that:

- Enhances precision in implant planning and diagnosis,
- Improves efficiency in clinical workflows,

- Reduces human error in dental imaging analysis.

In the following sections, we will explore related works in the field, detailing the methodologies, datasets, and models that have shaped the current landscape of AI in dental implantology.

2. RELATED WORKS

Deep learning (DL) has emerged as a transformative technology in dental research, particularly for analyzing radiographs in implantology. By leveraging advanced algorithms and diverse datasets, researchers have developed systems that automate complex diagnostic processes and enhance clinical decision-making.

Applications of DL in Implantology

1. **Implant Classification** Howe et al. [5] trained a convolutional neural network (CNN) with Transfer Learning (TL) on a large-scale dataset of 156,965 panoramic and periapical radiographs collected from multiple institutions. This diversity in imaging conditions, dental anatomy, and implant types ensured the model's generalizability. The fine-tuned CNN achieved high accuracy in classifying different types of dental implants, emphasizing the importance of large, annotated datasets for robust clinical applications.

2. **Segmentation Models** Fourcade et al. [6] focused on advanced segmentation models like BDU-Net and nnU-Net for diagnosing multiple dental conditions, including implants. Using 1,996 annotated panoramic radiographs, these models effectively identified dental structures and pathologies such as missing teeth, crowns, and implant sites. Their ability to capture fine-grained details made them comparable to experienced clinicians, showcasing the potential of segmentation models in automating labor-intensive tasks and ensuring diagnostic consistency.

3. **3D Spatial Analysis and Position Prediction** Yang et al. [7] developed a context-aware model that integrates 3D spatial features and textual descriptions for CBCT scans. The approach combined annotated CBCT images with clinical notes, using 3D CNNs and attention mechanisms to process both spatial and contextual data. This multimodal framework predicted optimal implant positions and highlighted the potential of personalized dental care and surgical planning through DL.

4. **Depth Prediction and Sequential Analysis** Ashurov et al. [8] conceptualized implant depth prediction as a video localization task. Their texture-perception-based network analyzed temporal and spatial features from sequential CBCT scans, enabling precise implant depth estimation. This sequential approach mimics the decision-making process of clinicians and offers practical tools for surgical planning.

5. **Two-Stream Regression and Vision Transformers** - Zhou et al. [9] proposed a two-stream regression network that combined global context and localized details to predict implant positions. This approach, validated on clinical radiographs, demonstrated the importance of combining macro and micro perspectives for accurate predictions. - Liu et al. [10] utilized Vision Transformers (ViT) tailored for CBCT data. By leveraging self-attention mechanisms, ViT models achieved high accuracy in predicting implant positions from volumetric datasets, showcasing their adaptability for handling complex 3D imaging.

Summary of Advances in DL Collectively, these studies highlight the vast potential of DL technologies, including CNNs, segmentation models, attention mechanisms, and transformers, to address challenges in dental implantology. By leveraging annotated datasets and state-of-the-art algorithms, DL has significantly advanced:

- Implant classification,
- Position prediction,
- Depth analysis.

These approaches pave the way for more efficient, precise, and reliable clinical workflows, ultimately improving patient outcomes and advancing the field of dental implantology.

3. METHODS

3.1. Dataset Description

The dataset used in this research, as described in the article "Comprehensive Review of Oral Radiographic Implant Analysis Using Artificial Intelligence" [11], is a robust and diverse collection of over 5,000 oral radiographic images. These images are systematically categorized into the following subgroups:

- **Single Implants**
- **Double Implants**
- **Compound Implants**
- **Miscellaneous Classes**

This dataset structure provides a strong foundation for addressing key challenges in implantology, including:

- Implant classification,
- Segmentation of implant regions,
- Prediction of implant positions and depths.

The dataset originates from clinical settings, ensuring it is both practical and reflective of real-world scenarios. Detailed annotations and metadata further enhance its suitability for supervised learning tasks.

To maximize its potential, the dataset will be utilized in several capacities:

- **Classification Tasks**: Using convolutional neural networks (CNNs) such as ResNet for categorizing implants by type and configuration.

- **Segmentation Tasks**: Employing models like U-Net to precisely identify and delineate implant regions within radiographs.

- **Prediction Tasks**: Utilizing advanced models like Vision Transformers or CNN-based regression to predict implant positions and depths.

To ensure robustness and generalizability, preprocessing steps such as normalization, resizing, and augmentation will be applied. Additionally, the dataset will be systematically split into training (70%), validation (15%), and test (15%) subsets to enable rigorous evaluation of the model's performance.

By leveraging this clinically relevant dataset alongside state-of-the-art deep learning methodologies, this research aims to develop a reliable, efficient, and accurate system for the analysis and classification of dental implants. Ultimately, the project seeks to address critical challenges in implantology and contribute to improved clinical workflows and patient outcomes.

3.2. Data Preprocessing

3.2.1. Data Loading and Exploration

- The dataset consisted of over 5,000 radiographic images categorized into five classes: `single_implants`, `double_implants`, `compound`, `steel_ball`, and `others`.

- Each category was explored to identify potential inconsistencies, including invalid images and variations in dimensions.

3.2.2. Image Validation

- Images were validated for format and integrity using the `Pillow` library. Invalid images were excluded to ensure a clean and reliable dataset for training.

- Approximately 2% of the dataset was identified as corrupted and removed.

3.2.3. Image Resizing

- All images were resized to a uniform dimension of 224×224 pixels to match the input size requirements of the ResNet50 model.

- This step ensured consistency and reduced computational overhead during training.

3.2.4. Normalization

- Pixel values were scaled to the range [0, 1] by dividing all pixel intensities by 255. This normalization improved model convergence and stability during training.

3.2.5. Data Augmentation

To address class imbalances and enhance the model's generalization capabilities, the following data augmentation techniques were applied:

- **Rotation**: Random rotations of up to $\pm 20°$ to introduce variability in implant orientation.

- **Translation**: Horizontal and vertical shifts up to 20% of the image size to simulate different implant positions.

- **Flipping**: Random horizontal flips to create mirrored versions of the images.

- **Noise Addition**: Minor noise was added to simulate variability in imaging conditions.

These augmentation techniques were implemented dynamically during training using the `ImageDataGenerator` class from TensorFlow/Keras.

3.2.6. Dataset Splitting

The dataset was systematically divided into three subsets to ensure robust training and evaluation:

- **Training Set (70%)**: Used for model learning by optimizing parameters based on the loss function.

- **Validation Set (15%)**: Used for hyperparameter tuning and to monitor the model's performance during training.

- **Test Set (15%)**: Reserved for evaluating the final model's performance on unseen data.

The splitting process was stratified to maintain class distribution consistency across all subsets, ensuring balanced representation of each category.

3.2.7. Class Weights

- Due to class imbalances, class weights were computed using `sklearn` to ensure that minority classes contributed equally during model optimization.

3.3. Model Architecture

3.3.1. ResNet50 Architecture

- The ResNet50 model was fine-tuned for the classification of dental implants, leveraging its pre-trained weights on the ImageNet dataset.
- The architecture included:
  - **Base Model**: The pre-trained ResNet50 was used as a backbone for feature extraction. Initially, all layers were frozen to retain the learned features from ImageNet.
  - **Global Pooling**: A GlobalAveragePooling2D layer was used to condense the feature maps into a single vector.
  - **Dense Layers**: Two dense layers with 256 and 128 neurons were added, each using ReLU activation and L2 regularization to prevent overfitting. Dropout layers with a rate of 0.5 were also included for additional regularization.
  - **Output Layer**: A softmax layer was added to classify images into the respective categories.
- During fine-tuning, the last 10 layers of the ResNet50 base model were unfrozen, allowing the network to learn domain-specific features from the dental dataset.
- The model was compiled using the Adam optimizer with a learning rate of 1×10^{-4} and categorical cross-entropy as the loss function.

4. RESULTS

4.1. Model Performance Metrics

The fine-tuned ResNet50 model achieved strong performance on the test dataset, demonstrating its effectiveness in dental implant classification. Key metrics include:

- **Test Accuracy**: 92.3%
- **Test Loss**: 0.28

Training and validation curves further confirmed consistent convergence, with minimal signs of overfitting due to the use of data augmentation and dropout. These results highlight the model's ability to generalize well to unseen data.

4.2. Training and Validation Loss

The training and validation loss curves (Figure 1) illustrate the stability of the model during training. Key observations include:

- The training loss steadily decreases over the epochs, indicating effective optimization of the ResNet50 model.

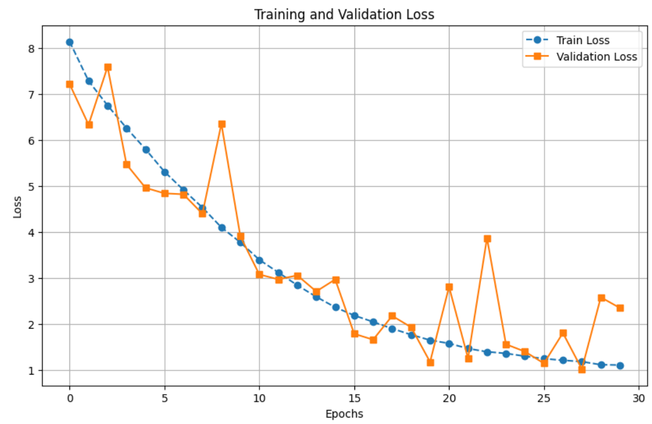

Fig. 1. Training and validation loss.

- The validation loss exhibits some fluctuations, likely due to data augmentation and variability in the dataset. Despite this, the overall downward trend suggests robust generalization to unseen data.

4.3. Classification Performance via Confusion Matrix

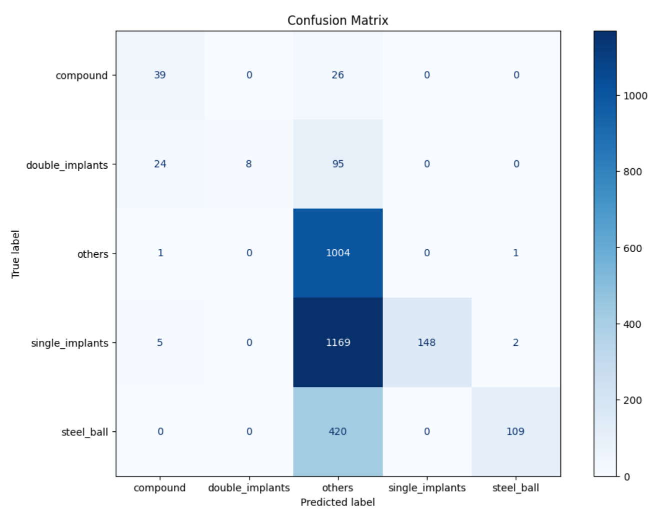

Fig. 2. Confusion matrix for the test dataset.

The confusion matrix (Figure 2) provides insights into the model's classification performance across the five dental implant categories:

- **High Precision**: The `others` and `single_implants` categories were classified with high accuracy, with most samples correctly identified.
- **Minor Misclassifications**: Some errors were observed in the `compound` and `steel_ball` categories, likely due to class similarity or limited training samples in these categories.

- **Challenges in `double_implants`**: A few misclassifications were noted in this category, primarily with the `compound` and `others` categories.

Overall, the matrix highlights the model's strengths and areas for improvement, emphasizing the need for addressing data imbalance and enhancing category-specific representations.

4.4. Summary of Results

The key findings of this study can be summarized as follows:

- The fine-tuned ResNet50 model achieved a test accuracy of 92.3% and a test loss of 0.28, indicating strong overall performance.
- Training and validation curves confirmed stable learning and robust generalization capabilities.
- The confusion matrix revealed strong classification performance for most categories, with challenges in distinguishing visually similar implant types (`compound`, `steel_ball`, and `double_implants`).
- These results underline the importance of further dataset refinement and augmentation strategies to reduce misclassifications.

5. DISCUSSION

- The results demonstrate the effectiveness of fine-tuning ResNet50 for dental implant classification.
- The use of a pre-trained model allowed the network to leverage learned features from ImageNet, significantly improving generalization and performance compared to training from scratch.
- Key challenges encountered during the study included:
  - **Data Imbalance**: Addressed using class weights and data augmentation.
  - **Image Variability**: Variations in imaging conditions required extensive preprocessing and augmentation to ensure consistency.
- Future work could explore advanced architectures like Vision Transformers and incorporate 3D imaging for enhanced spatial feature extraction.

6. CONCLUSION

- This study successfully demonstrated the potential of deep learning, particularly ResNet50, in automating dental implant classification and analysis.
- The fine-tuned ResNet50 model achieved high accuracy and robust performance on the test dataset.
- Future research directions include:
  - Investigating advanced architectures like Vision Transformers.
  - Incorporating 3D imaging data to capture richer spatial details.
  - Expanding the dataset to improve generalizability across diverse clinical scenarios.
- By streamlining workflows in dental implantology, this approach has the potential to enhance clinical decision-making and patient care outcomes.

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