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Original Research

Embracing Computer Vision for Diagnostic Maxillofacial Imaging — An Artificial Intelligence Machine Learning (AIML)Pilot Project

Oladimeji Adeniyi Akadiri[1], *Kesiena Seun Yarhere[1]

[1]Department of Oral and Maxillofacial Surgery, Faculty of Dentistry. College of Health Sciences. University of Port Harcourt, Rivers State, Nigeria

Abstract

Background: Artificial intelligence (AI) is rapidly transforming healthcare, particularly in diagnostic medical imaging. For Nigerian Oral and Maxillofacial surgeons, embracing AI technologies is essential to improve diagnostic accuracy and maintain global relevance. This study aimed to demonstrate the potential of machine learning (ML) tools in enhancing diagnostic precision in maxillofacial radiology.

Methodology: A supervised learning model was developed using Google's Teachable Machine, a no-code ML platform based on computer vision. Radiological images of histologically confirmed lesions were retrieved. Two projects were conducted: Project 1 trained the model to distinguish between malignant and benign bony jaw lesions using 46 radiographs (panoramic and sectional CT images). Project 2 trained the model to differentiate between craniofacial fibrous dysplasia and ossifying fibroma, using 40 radiographs. Each model was tested on five new images. The output probabilities were analyzed, and standard performance metrics—accuracy, precision, recall (sensitivity), and F1-score—were computed. Additionally, ROC-AUC (Receiver Operating Characteristic – Area Under the Curve) curves were generated using Python code on Google Colaboratory IDE.

Results: In Project 1, the model yielded predictive probabilities ranging from 89% to 100% for distinguishing malignant from benign lesions. In Project 2, it produced 71% to 100% probabilities for classifying fibrous dysplasia versus ossifying fibroma. Applying a 70% probability threshold for positive prediction, both models achieved perfect scores (1.0) across all performance metrics, including AUC = 1.00.

Conclusion: AI-driven computer vision models show strong potential for improving diagnostic workflows in maxillofacial imaging. Their application can support more efficient clinical decision-making. However, the use of small test samples may have resulted in overfitting. Future studies with larger datasets and increased AI literacy among clinicians are essential for real-world implementation in resource-limited settings.

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Computer Vision, Maxillofacial Imaging, Diagnostic Efficiency.

***Correspondence:** Kesiena Seun Yarhere, Department of Oral and Maxillofacial Surgery, Faculty of Dentistry. College of Health Sciences. University of Port Harcourt, Rivers State, Nigeria. **Email:** askkes@gmail.com

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Quick Response Code:

Introduction

Artificial intelligence (AI) is revolutionizing the world, impacting diverse fields, with healthcare among the most significantly affected sectors. In medical imaging, AI has demonstrated notable success in diagnostic accuracy, speed, and consistency, particularly through machine learning (ML) and its subset, computer vision. This subset employs deep learning algorithms, such as convolutional neural networks (CNNs), for image analysis, identification, and classification tasks, making it increasingly valuable for detecting conditions in medical and surgical domains [1,2,3].

In recent years, computer vision has gained traction in advanced healthcare systems, improving efficiency in fields such as radiology and histology by facilitating diagnostic imaging processes and enabling earlier detection of conditions [3,4]. However, AI adoption in Nigerian healthcare remains limited, particularly in specialties like dentistry and oral and maxillofacial surgery. This lag presents a unique opportunity to explore AI-driven tools that can support diagnostic workflows and inspire further interest in AI applications among practitioners. The present study leverages Google's Teachable Machine, a no-code ML tool, to train models for classifying radiological images of maxillofacial lesions. Specifically, it focuses on identifying benign versus malignant lesions and distinguishing fibrous dysplasia from ossifying fibroma.

The Teachable Machine is a web-based platform that enables users to create custom machine learning (ML) classification models without requiring any coding skills. By utilizing inputs such as images, webcam, and audio, the platform leverages transfer learning—a technique that builds pre-trained models—to recognize patterns and features within the data. This approach allows users to quickly generate functional classification models by retraining a base model originally trained on a large dataset within a specific domain [5]. Machine learning involves the use of algorithms to analyze data, discover patterns, and make decisions or predictions based on the analysis. [3,6] Deep learning is a type of machine learning that uses an artificial neural network (ANN), a computer system inspired by how the human brain works. The ANN is multilayered**,** and each layer consists of different information concerning the data. The system goes through important steps when classifying data, which are feature selection, feature extraction, and then classification [6,7]. CNN, a specialized type of ANN, is designed for pattern recognition across image, sound, and language inputs, hence well suited for medical imaging and spatial data. They automatically detect and learn features from raw data. Also, CNNs need fewer parameters than traditional ANNs, meaning they are often faster and easier to train.[6]

Teachable Machine uses transfer learning, which adopts the technique of feature extraction from a pre-trained model; this eliminates the need for developers to start over when training a model. A Transfer Learning model is typically trained on a large dataset like ImageNet, and the related parameters obtained from the trained model can then be used with a custom neural network for any other related application [6,8]

The Google Teachable Machine uses MobileNet as a base model for image classification tasks. The MobileNet, which is already trained on the ImageNet dataset, is lightweight and fast, allowing for an in-browser application [9]. In Teachable Machine, its final layers are removed and replaced with a custom classifier that is trained directly in the browser using the user's input data. The trained model can be exported in multiple TensorFlow-compatible formats: TensorFlow.js for in-browser execution or integration into JavaScript-based applications; TensorFlow Lite for deployment on resource-constrained environments such as Android or embedded systems; and the TensorFlow Saved Model format for use within Python-based environments, enabling further training or inference.[9]

Google Teachable Machine has been successfully employed across various fields, showcasing its versatility and innovative applications.[10,11,12] Artificial intelligence is transforming medical imaging, as deep learning techniques now enable functions like image reconstruction, triage, computer-aided classification, and detection to match or outperform expert radiologists.[13] However, the application of Google's teachable machine in Healthcare is yet to be widely tested. This pilot project is arguably a pioneering effort to introduce computer vision to radiodiagnosis in the oral and maxillofacial domain in Nigeria.

Methods

Ethical clearance: Ethical approval for the study was obtained from the Research and Ethics Committee of the University of Port Harcourt Teaching Hospital. UPTH/ADM/90/S.11/VOL.XI/1920 Study Design: This study adopted a diagnostic accuracy design using a prospective in vitro approach to evaluate the effectiveness of a no-code machine learning platform in classifying maxillofacial radiological lesions.

Inclusion Criteria: The inclusion criteria were Only radiological images (panoramic and sectional CT) of lesions with confirmed histopathological diagnoses were included; Images selected possessed sufficient resolution and clarity, suitable for AI model training; The dataset was limited to lesions involving the maxilla, mandible, or craniofacial bones and only hard tissue (bony) lesions were considered for inclusion in the study.

Exclusion criteria: The exclusion criteria were Cases with mixed pathologies; Images without a confirmed histologic diagnosis; Soft tissue lesions of the craniofacial region and Images with Poor quality

Procedure

Two distinct projects were undertaken to assess the model's diagnostic capabilities:

Project 1: Classification of Malignant vs. Benign Jaw Lesions

The Google Teachable Machine was trained to differentiate between malignant and benign jaw lesions based on radiological images. A total of 20 histologically confirmed malignant cases and 26 benign cases were randomly selected. Each case was identified using only the medical record number (MRN) to ensure confidentiality and protect patient privacy.

Associated radiological images were retrieved from the departmental archive using the MRN. Only high-quality sectional CT scans and panoramic radiographs**,** without enhancement, were selected for training. These images were categorized into two folders labeled "Malignant" and "Benign" and uploaded to the Google Teachable Machine for a binary classification task**,** which leveraged its embedded pre-trained convolutional neural network (CNN)**.**

Hyperparameters such as the number of epochs, batch size, and learning rate were manually adjusted to enhance model performance while reducing risks of overfitting or underfitting**,** thereby optimizing predictive accuracy (see Figure 1).

For validation, five new images (three malignant and two benign) were randomly selected and stored in a separate "Test Folder." These were used to assess the model's prediction accuracy.

Project 2: Differentiation Between Ossifying Fibroma and Fibrous Dysplasia

Project 2 followed the same protocol as Project 1 but focused on differentiating between two similar benign lesions**:** ossifying fibroma and fibrous dysplasia**.**

Radiological images from 20 cases of ossifying fibroma and 20 cases of fibrous dysplasia were categorized and uploaded into their respective folders. The model was then trained using the supervised learning process available on the Google Teachable Machine. A separate test set comprising five new images**,** randomly selected (from both lesion types), was used to evaluate the model's classification performance for this second task.

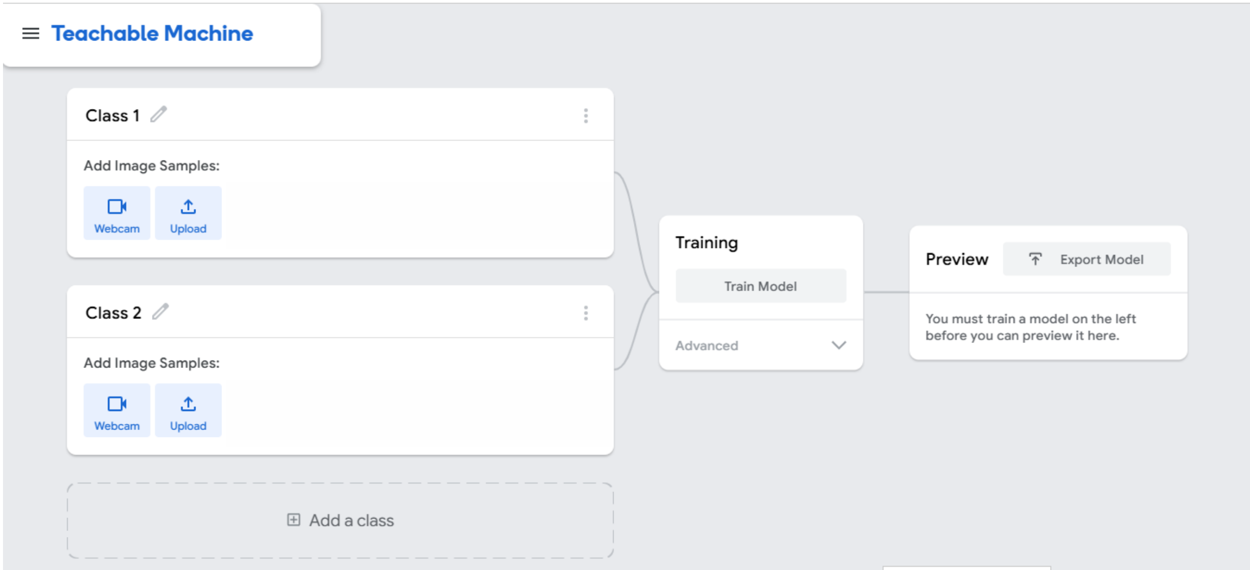

Fig.1: Google Teachable Machine training interface showing multiple classification task possibilities. (*Source: www.teachablemachine.withgoogle.com*)

Statistical Analysis

The models' predictive outputs were evaluated based on standard performance metrics: accuracy, precision, recall (sensitivity), F1-score, and area under the receiver operating characteristic curve (ROC-AUC). ROC-AUC analysis was conducted using Python (version 3.13.3) within the Google Colaboratory integrated development environment (IDE).

Results

In Project 1, the model was trained with 26 benign and 20 malignant radiological images, while Project 2 utilized 20 images each for ossifying fibroma and fibrous dysplasia. The training durations were approximately 10 minutes for Project 1 and 12 minutes for Project 2.

In Project 1, the model accurately differentiated between malignant and benign lesions, outputting predictive probabilities ranging from 89% to 100% for the correct class [Table 1]. It displayed complete certainty (100%) in two cases. For the remaining three test images, the model assigned 98%, 95%, and 89% probabilities to the correct diagnoses, with the residual percentages attributed to the incorrect class.

Table 1: Malignant vs Benign bony lesion - Project 1 Model predictions

IMAGE SLIDE	MODEL REPORT		ACTUAL [HCIC]
	Malignant (%)	Benign (%)	
SLIDE 1	0	100	Benign
SLIDE 2	89	11	Malignant
SLIDE 3	100	0	Malignant
SLIDE 4	2	98	Benign
SLIDE 5	95	5	Malignant

HCIC: Histologically confirmed image classification

In **Project 2** [Table 2], the model produced probabilities ranging from **71% to 100%** for the correct lesion classification. The residual probability in each case was attributed to the incorrect class, consistent with binary prediction outputs.

Table 2. Fibrous dysplasia vs Ossifying fibroma - Project 2 Model predictions

IMAGE SLIDE	MODEL REPORT		ACTUAL [HCIC]
	Fibrous dysplasia(%)	Ossifying fibroma(%)	
SLIDE 1	79	21	Fibrous dysplasia
SLIDE 2	17	83	Ossifying fibroma
SLIDE 3	94	6	Fibrous dysplasia
SLIDE 4	0	100	Ossifying fibroma
SLIDE 5	71	29	Fibrous dysplasia

Performance metrics—including accuracy, precision, recall, and F1-score—were computed using confusion matrix values (Figure 2) through Python code executed in Google Colaboratory**.** Both models achieved perfect performance**,** scoring 1.00 across all metrics**.** A combined ROC curve was generated (Figure 3), and the Area Under the Curve (AUC) for both models was 1.00**,** indicating perfect class discrimination based on the limited test samples used in this pilot study.

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Confusion Matrix Values		
TP (True Positives): Correctly predicted positive cases. TN (True Negatives): Correctly predicted negative cases. FP (False Positives): Incorrectly predicted positive cases. FN (False Negatives): Incorrectly predicted negative cases.	Model 1: TP = 3 (Malignant correctly identified) TN = 2 (Benign correctly identified) FP = 0 (No false positives) FN = 0 (No false negatives)	Model 2: TP = 3 (Fibrous Dysplasia correctly identified) TN = 2 (Ossifying Fibroma correctly identified) FP = 0 (No false positives) FN = 0 (No false negatives)

Performance Metrics Formulae

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Figure 2: Confusion Matrix Values and Performance Metrics Formulae

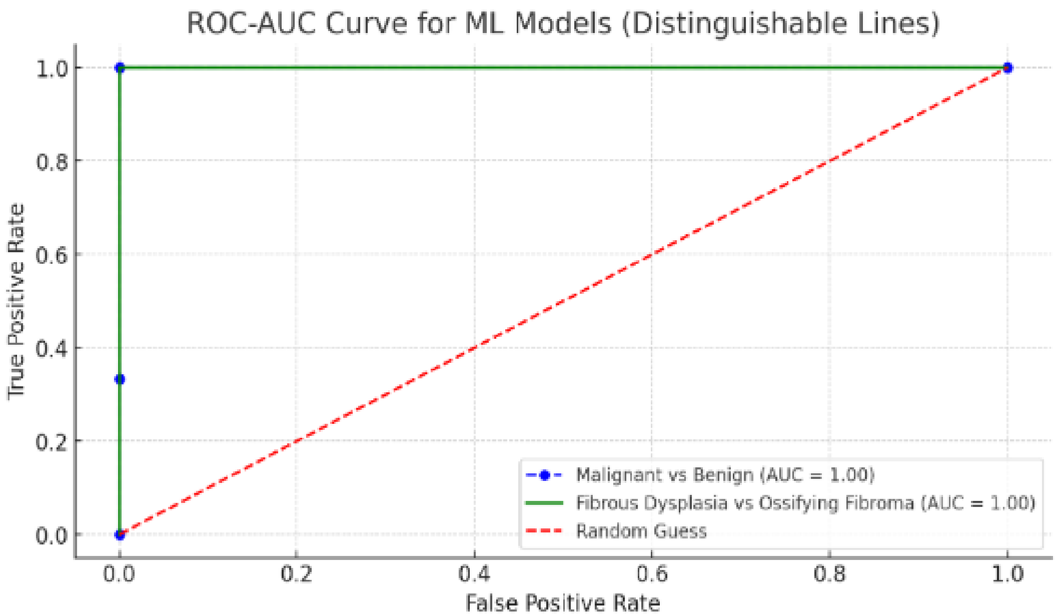

Figure 3: Combined ROC-AUC plot for the models.

In the ROC-AUC plot:

- The blue dashed line with circles represents the model distinguishing between malignant and benign lesions**.**
- The green solid line with crosses represents the model distinguishing between fibrous dysplasia and ossifying fibroma**.**

The ROC curves for both models perfectly overlap**,** confirming their identical and flawless performance (AUC = 1.0).

Discussion

The introduction of artificial intelligence (AI) into maxillofacial imaging represents a significant advancement in diagnostic and therapeutic standards. AI tools have the potential to enhance diagnostic accuracy, streamline clinical workflows, and optimize resource utilization, ultimately leading to improved patient outcomes and more efficient service delivery. Although the adoption of AI in Nigerian healthcare is currently limited, integrating AI-driven diagnostic tools into maxillofacial surgery could bridge existing gaps in diagnostic efficiency and address resource constraints.

According to the Oxford Insights Government AI Readiness Index (2023), Nigeria ranked 103rd out of 172 countries, lagging behind nations such as Benin, Rwanda, Kenya, Senegal, South Africa, and Mauritius [14]. While deep learning applications in oral and maxillofacial imaging have predominantly focused on cephalometric landmark detection, dental caries diagnosis, periodontitis detection, and maxillary sinusitis identification [15], there remains a notable paucity of data on the application of AI in the diagnostic imaging of maxillofacial tumors.

In our study, deep learning algorithms, particularly Convolutional Neural Networks (CNNs), enabled rapid and precise differentiation between benign and malignant lesions and between fibrous dysplasia and ossifying fibroma. This automated image analysis, which has proven successful in diagnosing breast, lung, and prostate cancers [16,17], demonstrated strong potential for improving diagnostic accuracy in maxillofacial surgery. A similar study by Poedjiastoeti and Suebnukarn (2018) [18] utilized CNNs to detect ameloblastoma and odontogenic keratocyst (OKC) using transfer learning from large datasets. The CNN model, pre-trained on ImageNet, showed comparable sensitivity, specificity, and accuracy to assessments by experienced maxillofacial surgeons, while significantly reducing analysis time from an average of 23.1 minutes to 38 seconds.

The performance of deep networks is significantly influenced by the volume and quality of training data. The accuracy of AI models can be greatly enhanced by using large, diverse, and high-quality image datasets. However, the collection of biomedical data often involves high costs and complexity, leading to limited dataset sizes and imbalanced class distributions. Transfer learning, an algorithmic technique that adapts models trained on large datasets to smaller, specialized ones, presents a viable solution for maximizing accuracy despite limited data [18].

While our study focused on binary differentiation of lesions, the use of a no-code platform, such as the Google Teachable Machine, enables comparison among multiple lesion types (Figure 1). Such platforms reduce barriers to AI integration, particularly in low-resource settings, by allowing healthcare professionals to develop AI applications without programming expertise. This approach is relevant in the Nigerian context, where healthcare professionals often lack access to specialized diagnostic tools. Consequently, expanding AI education among maxillofacial surgeons is crucial. Training initiatives that introduce basic AI concepts through accessible tools, such as Google Teachable Machine and TensorFlow, can foster innovation and improve diagnostic capabilities [20].

Our study demonstrated high predictive probabilities, with 89–100% accuracy in classifying benign versus malignant lesions and 71–100% accuracy in distinguishing fibrous dysplasia from ossifying fibroma. Both models achieved perfect performance metrics (AUC = 1.00), indicating strong potential for clinical application. Nevertheless, the pilot nature of the study and the small training and test sample size warrant cautious interpretation of these results. To validate the model's reliability, further research with larger and more varied datasets is necessary.

Key Insights and Limitations

Despite the ideal performance metrics, several factors might have contributed to these outcomes:

Small sample size (5 slides): Limits the model's ability to generalize to broader clinical scenarios.

Potential model overfitting: The model's high accuracy may reflect its familiarity with the limited data rather than its true generalization capacity.

High similarity between training and test data: Reduces variability and can falsely elevate performance metrics.

However, the study underscores the potential of AI-assisted diagnostic tools as effective adjuncts to traditional radiological interpretation in oral and maxillofacial surgery. These findings align with existing literature emphasizing the high sensitivity and specificity of AI in radiological applications [1,2,18].

Broader Applications and Future Directions

The application of AI in maxillofacial surgery extends beyond imaging. Technologies such as Natural Language Processing (NLP) and robotic-assisted surgery are becoming integral to surgical planning and patient education, supporting clinical decision-making. Moreover, machine learning algorithms can analyze complex data from electronic health records (EHRs) to predict complications or outcomes, enabling personalized treatment planning [19].

A key strength of our study is the utilization of a no-code AI platform, which makes machine learning accessible to healthcare practitioners without programming skills. This approach is particularly relevant in Nigeria, where the integration of AI in healthcare remains limited. Investing in AI literacy and training will empower maxillofacial surgeons to develop context-specific algorithms, addressing unique patient needs and healthcare challenges. Collaborative initiatives involving AI researchers and interdisciplinary training programs will further support the effective integration of AI into clinical practice.

Limitations and Future Research

One major limitation of advanced AI models, particularly CNNs, is their lack of interpretability. Often referred to as "black boxes", these models can produce accurate predictions without providing insight into their decision-making processes [21]. Research into Explainable AI (XAI) is critical for ensuring transparency and fostering clinician trust [22,23].

The small sample size used in this study likely contributed to overfitting. Future studies should increase dataset sizes and standardize image quality to ensure robust validation and generalizability of the model in real-world applications.

Conclusion

AI-powered computer vision models offer promising avenues for improving diagnostic accuracy in maxillofacial imaging, addressing diagnostic gaps within Nigeria's healthcare system. Embracing AI-driven tools and prioritizing AI education among healthcare practitioners will help maintain global relevance and advance clinical outcomes. Although further validation is essential, this pilot study supports the potential of AI in maxillofacial image diagnosis and encourages local practitioners to explore this evolving paradigm.

Conflict of Interest: The authors have no conflict of interest to declare

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