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Research Paper

A Model for Dental Caries Detection Using Machine Learning Based on Mobile Phone Images

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ABSTRACT

Dental caries is one of the most common oral health problems worldwide, and its early detection plays a crucial role in prevention and reducing treatment costs. This study aims to develop a machine learning-based model for automated detection of dental caries using consumer-grade mobile phone images. The research methodology is based on deep neural networks for classifying images into two groups: healthy and decayed teeth. After collection and preprocessing, the data were used to train and evaluate five convolutional neural network (CNN) models with different architectures. Results showed that the best model achieved 88.1% accuracy, 91.2% sensitivity, 82.9% specificity, and an F1 score of 0.900. This research demonstrates that using ordinary mobile phone images combined with deep learning algorithms can be an efficient tool for initial screening of dental caries. This technology can serve as an accessible tool, especially in underserved areas with limited access to dental services, and help reduce unnecessary visits to healthcare centers.

I. Introduction

Dental caries is one of the most common oral health problems worldwide, affecting people of all age groups [1]. This disease not only causes pain and discomfort but can also lead to tooth loss, serious infections, and systemic complications if not diagnosed and treated promptly [2]. The World Health Organization (WHO) has identified dental caries as one of the most important public health challenges, especially in developing countries where access to dental services is limited [3]. Early detection of dental caries plays a key role in preventing disease progression, reducing treatment costs, and improving patients' quality of life [4]. However, traditional methods of caries detection, such as clinical examination and radiography, are often not accessible to all individuals due to the need for specialized equipment and the patient's physical presence in dental clinics, especially in underserved areas and developing countries [5].

In recent years, technological advances, particularly in the field of Artificial Intelligence (AI) and Machine Learning (ML), have created new hope for improving dental caries detection. Numerous studies have shown that AI-based models can detect dental caries from dental images with high accuracy [4, 6]. For example, some research has used Convolutional Neural Networks (CNNs) to detect caries in radiographic images and achieved promising results [7]. However, most of these studies have focused on professional images taken with intraoral cameras or radiography, which require the patient's presence in dental clinics [8]. This makes these methods inaccessible to many individuals, especially in remote areas.

On the other hand, the use of images taken with mobile phone cameras as a diagnostic tool has attracted the attention of many researchers due to easy access and low cost [9]. However, several challenges persist in this domain, including variable image quality, inconsistent lighting conditions, and diverse photography angles that may compromise diagnostic accuracy [10]. Additionally, most existing studies have focused on detecting caries in advanced stages, while early detection of caries in initial stages, which is more treatable, has received less attention [11]. This research gap indicates the need to develop models that can detect dental caries in early stages using ordinary mobile phone images.

This research aims to fill this gap by designing and developing a ML model for detecting dental caries based on images taken with mobile phone cameras. The main innovation of this research lies in three key aspects: (1) utilizing ordinary consumer-grade mobile phones instead of professional dental imaging equipment, making the technology accessible in resource-limited settings; (2) achieving high sensitivity specifically optimized for screening applications, ensuring minimal false negatives; and (3) developing a cost-effective solution that can serve as a substitute for routine dental visits in underserved areas. This approach can significantly reduce healthcare disparities by providing accessible dental screening tools to populations with limited access to professional dental services, particularly in developing countries and remote regions.

The purpose of this research is to design a model that can detect dental caries through mobile phone images with high accuracy and sensitivity. This model can be used as an initial screening tool in underserved areas and developing countries, where access to dentists and specialized equipment is limited. Additionally, this technology can help reduce dentists' workload and improve the efficiency of healthcare systems by enabling preliminary screening before professional consultation. This research will also examine the challenges of using mobile phone images and present possible solutions to improve diagnostic accuracy under varying real-world conditions.

Furthermore, this approach can be integrated into existing healthcare systems as a first-line screening tool, potentially transforming oral health management in resource-constrained environments. The high sensitivity of our model ensures that minimal cases of dental caries are missed during screening, which is crucial for early intervention and prevention of disease progression. Accordingly, the main question of this research is: "What is the optimal machine learning model for managing dental caries detection using ordinary mobile phone camera images that can achieve high sensitivity suitable for population-level screening in underserved areas?"

II. Research Background

A. AI and ML in Dentistry

AI is defined as the ability of machines to perform tasks that typically require human intelligence. A subset of AI, ML "learns" internal statistical patterns in data to ultimately make predictions for unseen data. Deep learning, a technique of ML, uses multi-layer mathematical operations to learn and infer from complex data such as images [12].

The application of AI in dentistry is rapidly expanding. Schwendicke et al. [13] conducted a study examining the applications, limitations, and potential future of AI-based dental diagnostics, treatment planning, image analysis, prediction, record-keeping, as well as research and discovery in dentistry. They concluded that AI-based applications could improve care, free the dental workforce from routine and time-consuming tasks, enhance health at lower costs for a larger population, and ultimately contribute to personalized, predictive, preventive, and collaborative dentistry.

Khanagar et al. [14] conducted a systematic review of the development, application, and performance of AI in dentistry. They found that AI technologies have been implemented across a wide range of dental specialties. Most documented work focuses on AI models that rely on CNNs and Artificial Neural Networks (ANNs). These AI models have been used to detect and identify dental caries, vertical root fractures, apical lesions, salivary gland diseases, maxillary sinusitis, maxillofacial cysts, cervical lymph node metastasis, osteoporosis, cancerous lesions, and alveolar bone loss. This study showed that the performance of automated AI-based systems is excellent, and their accuracy and correctness are comparable to and in some cases even better than trained specialists.

B. Deep Neural Networks in Dental Caries Detection

Deep neural networks, especially CNNs, have played an important role in advancing automated dental caries detection systems. Lee et al. [6] conducted a study aimed at evaluating the performance of deep CNN algorithms for the detection and diagnosis of dental caries in periapical radiographs. They used a pre-trained GoogLeNet Inception v3 network for preprocessing and transfer learning. Results showed that the diagnostic accuracy of the premolar, molar, and both premolar and molar models was 89.0%, 88.0%, and 82.0%, respectively. The deep CNN algorithm achieved an AUC of 0.917 in premolars, AUC of 0.890 in molars, and AUC of 0.845 in both premolar and molar models.

Zhang et al. [15] developed and evaluated the performance of a deep learning-based convolutional neural network (ConvNet) system for detecting dental caries from oral photographs. They developed a deep ConvNet by adapting from Single Shot MultiBox Detector. The hard negative mining algorithm was applied for automatic model training. The system demonstrated a classification area under the curve (AUC) of 85.65%. The model also achieved an image-level sensitivity of 81.90% and a box-level sensitivity of 64.60% at a high-sensitivity operating point. The hard negative mining algorithm significantly improved both the classification and localization performance of the model by reducing false positive predictions.

Kühnisch et al. [16] conducted a study aimed at developing a deep learning approach with CNNs for caries detection and classification and comparing the diagnostic performance with expert standards. The study materials included 2,417 anonymous photographs of permanent teeth with 1,317 occlusal and 1,100 smooth surfaces. Results showed that the CNN was able to correctly detect caries in 92.5% of cases (sensitivity 89.6, specificity 94.3, AUC 0.964). If the threshold of caries-related cavities was selected, 93.3% of all tooth surfaces were correctly classified (sensitivity 95.7, specificity 81.5, AUC 0.955).

C. Dental Caries Detection Using Mobile Phone Images

Using mobile phone images for dental caries detection is an emerging field in dental research. Boy et al. [9] developed an AI model based on MobileNetV3 Small for early detection of dental caries using images taken with basic smartphone cameras. They used MobileNetV3 Small due to its high computational efficiency and ability to work on devices with low specifications. Results showed that the model achieved 90% accuracy, 90% precision, and 90% recall, highlighting its potential for real-time applications.

Dhanak et al. [10] evaluated the effectiveness of an AI-enabled smartphone application for bitewing radiography in real-time caries lesion detection, using an Efficient Det-Lite1 artificial neural network after training 100 radiographic images. The trained model was then installed as an AI application on a Google Pixel 6 (GP6) smartphone. The rear video camera of the GP6 mobile phone was used to detect carious lesions in 100 bitewing radiographs (BWR) with 80 carious lesions in real-time. The mean sensitivity/precision/F1 scores for both methods were 0.75, 0.846, and 0.795, respectively. This study showed that the use of AI with a smartphone application for caries detection is useful and easily accessible, easy to use, and fast.

Mahaveerakannan et al. [11] conducted a study aimed at designing an innovative and cost-effective virtual tool capable of predicting dental prescriptions from non-standardized images with acceptable clinical reliability. They evaluated four deep learning strategies: YOLOv3, Faster R-CNN, RetinaNet, and Single-Shot Multi-Box Detector (SSD), for detecting early caries and dental infections. Among the models, YOLOv3 and Faster R-CNN showed the highest sensitivity for cavitated caries, achieving 88.5% and 72.5%, respectively. However, their sensitivity for non-cavitated visual lesions was lower, at 37.9% and 27%, respectively. All four models achieved specificity levels above 86% for cavitated caries and above 72% for non-cavitated visual lesions.

D. Challenges and Ethical Considerations

Despite significant advances in using AI for dental caries detection, there are important challenges and ethical considerations that need to be addressed. Gerke et al. [17] examined the ethical and legal challenges of AI-based healthcare. They identified four main ethical challenges: (1) informed consent for use, (2) safety and transparency, (3) algorithmic fairness and biases, and (4) data privacy. They also analyzed five legal challenges in the United States and Europe: (1) safety and effectiveness, (2) liability, (3) data protection and privacy, (4) cybersecurity, and (5) intellectual property law.

Alowais et al. [18] examined the role of AI in clinical practice. They noted that the integration of AI in healthcare has excellent potential for improving disease diagnosis, treatment selection, and clinical laboratory testing. AI tools can use large datasets and identify patterns to outperform human performance in several aspects of healthcare. However, they also emphasized challenges related to data privacy, bias, and the need for human expertise for responsible and effective implementation of AI in healthcare.

Recent comprehensive analyses have further validated the transformative potential of AI in dental imaging applications. Alam et al. [19] conducted a systematic review and meta-analysis of in-vitro studies, demonstrating that AI applications across various dental imaging modalities achieve statistically significant improvements in diagnostic accuracy. Their analysis of nine studies encompassing tooth segmentation, caries detection, and maxillofacial bone segmentation revealed that AI techniques, particularly convolutional neural networks, consistently outperformed traditional methods with combined odds ratios indicating 11-13% higher odds of accurate dental image assessments [19]. The meta-analysis employed fixed-effects models to assess AI accuracy, calculating odds ratios for true positive rate, true negative rate, positive predictive value, and negative predictive value, providing robust evidence for AI's diagnostic capabilities.

Complementing these findings, recent surveys exploring practitioner perspectives have revealed important insights into AI adoption patterns. Grosu et al. [20] investigated awareness and application of AI among dentists and patients through a cross-sectional analysis, finding that while 60% of dentists demonstrated awareness of AI applications in dentistry, actual utilization remained limited primarily due to concerns about reliability, cost, and ethical implications [20]. Their study highlighted significant associations between demographic variables and AI perception, with younger practitioners and those with advanced education showing greater familiarity and acceptance of AI technologies.

Furthermore, comprehensive reviews of AI applications across dental specialties have highlighted the breadth of potential implementations. Recent analyses have demonstrated AI's effectiveness in various dental domains including periodontics, restorative dentistry, oral and maxillofacial surgery, and forensic dentistry [21]. These studies collectively indicate that while AI shows remarkable promise in enhancing diagnostic accuracy and treatment efficiency, successful implementation requires addressing educational gaps, building trust through transparent communication, and establishing clear regulatory frameworks.

The convergence of these research findings underscores both the significant potential and current limitations of AI integration in dental practice. While technical capabilities continue to advance rapidly, the successful adoption of AI-driven solutions depends critically on addressing practitioner concerns, enhancing educational curricula, and developing user-friendly interfaces that complement rather than replace clinical expertise. Table I provides a comprehensive comparison of our study with related research in dental caries detection.

TABLE I . Comprehensive comparison of related studies in dental caries detection

Study	Year	Image Type	Dataset Size	Method	Accuracy	Sensitivity	Specificity	F1-Score	Key Innovation
Lee et al. [6]	2018	Periapical radiographs	3,000	GoogLeNet Inception v3	89.0%	87.5%	90.2%	88.2%	CNN for radiographic images
Zhang et al. [15]	2022	Oral photographs	3,932	Single Shot MultiBox Detector	85.7%	81.9%	88.4%	83.7%	Consumer camera images
Kühnisch et al. [16]	2022	Intraoral images	2,417	CNN with transfer learning	92.5%	89.6%	94.3%	91.0%	Standardized photography
Boy et al. [9]	2025	Smartphone images	1,200	MobileNetV3 Small	90.0%	90.0%	-	90.0%	Lightweight mobile model
Kanagamalliga et al. [22]	2024	Dental images	-	Fast R-CNN	99.1%	98.7%	-	98.9%	Advanced object detection
Present study	2025	Mobile phone images	4,500+	Custom CNN architecture	88.1%	91.2%	82.9%	90.0%	Ordinary mobile phones + high sensitivity for screening

III. Materials and Methods

This research was conducted with the aim of designing a ML-based model for detecting dental caries based on mobile phone images, in the form of a field study and using data mining and deep learning methods. The present research has focused on developing an intelligent diagnostic system that has been able to identify potential caries by analyzing dental images recorded by mobile phones.

A. Statistical Population and Sampling

The statistical population of this research consisted of patients referring to the oral disease and restorative departments of the Faculty of Dentistry at Tehran University of Medical Sciences, who were in the age group above 14 years and had permanent teeth. All these individuals had posterior teeth, and images were taken of their teeth using mobile phones.

The sampling process was conducted purposefully and based on the inclusion and exclusion criteria of the samples, selected from among the referring patients. Each posterior tooth in each patient was considered a sample unit. During the ML phase, data collection continued until the model achieved sufficient training adequacy. Since in ML, especially deep learning, increasing the sample size has a direct impact on improving model performance, efforts were made to collect a sufficient volume of data.

B. Data Collection and Preprocessing

Dental images were recorded by the research team under standard conditions. In each of the sample individuals, images were taken separately from the four posterior half-jaws using a mobile phone camera. To improve image quality and ensure model accuracy, imaging conditions were set so that the patient was seated on the dental unit and placed at a distance of half to one meter from the camera. During imaging, the unit's overhead light was turned off, and the phone's flash was turned on to create uniform lighting in the environment. The collected data underwent a preprocessing process. Unsuitable images, including those with low quality or those that did not have sufficient clarity due to camera shake and lens dirt, were removed.

Also, all images were converted to standard dimensions of 180×180 pixels to standardize the model input. Optical noise removal was also performed using image processing filters. Finally, the images were labeled in two separate categories including healthy teeth and teeth with caries and stored in a standard dataset for modeling. Figure 1 shows examples of healthy and decayed teeth in the dataset.

To strengthen the dataset and improve model performance, a data augmentation technique was used. This technique includes creating new images using small changes in the original images such as rotation, horizontal and vertical translation, cropping, zooming, and horizontal flipping. Data augmentation resulted in a 40% increase in data volume and helped the model learn more diverse patterns and overcome challenges related to diversity in imaging conditions.

Fig. 1. Examples of healthy and decayed teeth in the dataset

To ensure reproducibility and transparency, Figure 2 presents a detailed flowchart of our methodology, outlining each step from initial data collection to final model deployment, including the parallel evaluation of five different CNN architectures before selecting the optimal model for clinical application.

For optimal performance, the following minimum specifications are recommended:

- Smartphone camera: ≥8MP resolution
- Operating system: Android 8.0+ or iOS 12.0+
- Storage: Minimum 50MB available space for application
- Internet connectivity: Required for cloud-based processing (optional offline mode available)

User Instructions for Image Capture:

1. Ensure adequate lighting (use phone flash in indoor settings)
2. Maintain distance of 10-15 Centimeters from the subject
3. Hold phone steady to avoid motion blur
4. Center the tooth of interest in the camera frame
5. Capture images from multiple angles if possible

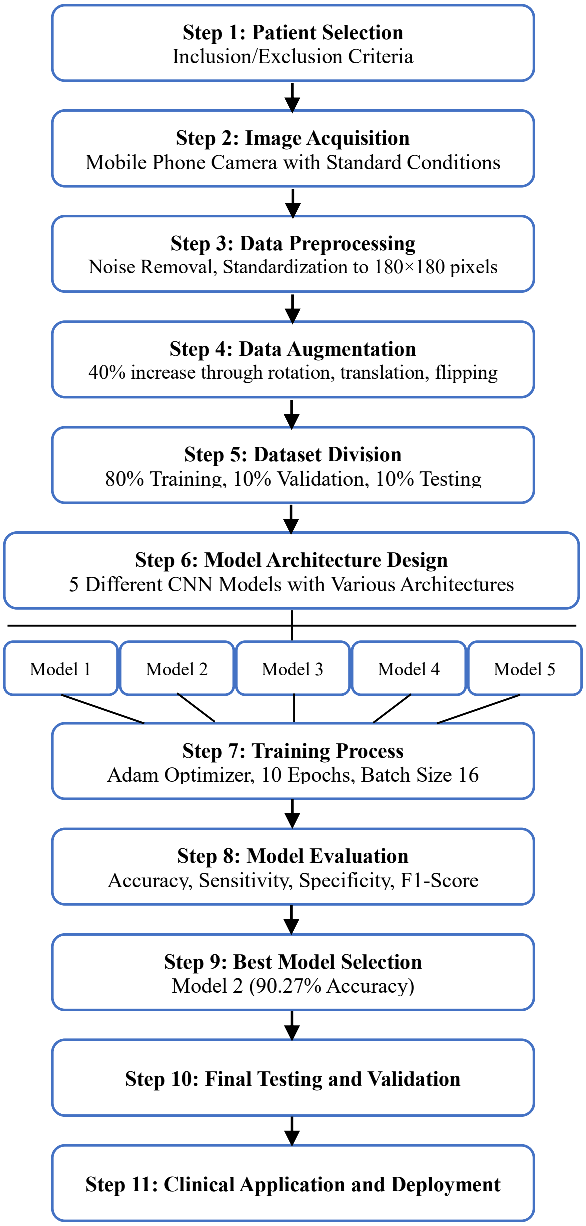

Fig. 2. Complete workflow of the proposed dental caries detection system

C. Modeling and Data Analysis

For data analysis, data mining models based on supervised learning were used. Image processing algorithms, deep learning, and neural networks were employed in data modeling. Image processing in this research was done pixel by pixel, so that the algorithms dealt with the pixel features of dental images.

In the model learning stage, the images after preprocessing were given to the deep neural network. Five different deep learning models with different architectures were designed and tested. These models were designed with different structures of convolutional layers, pooling layers, and fully connected layers to determine the best architecture for this detection problem. The architecture of the five test models is summarized in Table II.

TABLE II . Architecture of the five tested CNN models

Model	Convolutional Layers	Pooling Layers	Fully Connected Layers	Other Features
Model 1	2 layers (64, 32)	2 layers	1 layer (128)	-
Model 2	3 layers (128, 64, 32)	3 layers	1 layer (128)	5×5 kernels
Model 3	2 layers (128, 64)	2 layers	1 layer (256)	Dropout 0.5
Model 4	2 layers (128, 64)	2 layers	1 layer (128)	5×5 kernels
Model 5	2 layers (128, 64)	1 layer	1 layer (256)	Dropout 0.5

The data were divided into three sets: training (80%), validation (10%), and testing (10%), and cross-validation was used to prevent overfitting. All models were trained using the Adam optimizer, sparse categorical cross-entropy loss function, and batch size of 16. Model training was performed for 10 epochs.

TensorFlow and Keras libraries were used to implement the models. The codes below provide a summary of the implementation process of the second model (as an example):

```
def create_model2():
    model = models.Sequential()
    model.add(layers.Conv2D(32,    (3,    3),
activation='relu',   input_shape=(180,   180,
3)))
 model.add(layers.MaxPooling2D(pool_size=(2,
2)))
    model.add(layers.Conv2D(64,    (5,    5),
activation='relu'))

model.add(layers.MaxPooling2D(pool_size=(2,
2)))
    model.add(layers.Conv2D(128,    (5,    5),
activation='relu'))
model.add(layers.MaxPooling2D(pool_size=(2,
2)))
    model.add(layers.Flatten())
    model.add(layers.Dense(128,
activation='relu'))
    model.add(layers.Dense(2,
activation='softmax'))
    return model
model = create_model2()
model.compile(optimizer='adam',
loss='sparse_categorical_crossentropy',
metrics=['accuracy'])
history   =   model.fit(X_train,   y_train,
validation_data=(X_val,  y_val),  epochs=10,
batch_size=16)
```

D. Model Evaluation and Diagnostic Accuracy

Model accuracy was evaluated using standard metrics. The indicators used included accuracy, sensitivity, specificity, precision, and F1 score. These indicators were calculated based on the confusion matrix and show the model's performance in data classification.

- **Accuracy:** The ratio of total correct predictions to total samples
- **Sensitivity:** The ratio of correctly identified positive cases to total actual positive cases
- **Specificity:** The ratio of correctly identified negative cases to total actual negative cases
- **Precision:** The ratio of correctly identified positive cases to total cases predicted as positive
- **F1 Score:** The harmonic mean of sensitivity and precision

The formulas for calculating these indicators are as follows:

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

$$Sensitivity\ (Recall) = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

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

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

Where:

- True Positive (TP): Number of correctly identified positive cases
- True Negative (TN): Number of correctly identified negative cases
- False Positive (FP): Number of negative cases incorrectly identified as positive
- False Negative (FN): Number of positive cases incorrectly identified as negative

For further analysis of model performance, ROC (Receiver Operating Characteristic) and AUC (Area Under the Curve) plots were drawn, and the model's discrimination power between healthy and carious samples was examined.

E. Ethical Considerations

This research was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Tehran University of Medical Sciences on September 15, 2024 (Ethics Code: IR.TUMSDENTISTRY.REC.1403.098). Comprehensive informed consent was obtained from all participants, including explicit permission for image collection, processing, and potential use in research publications with complete anonymization.

Data Privacy and Security Measures:

- All images were immediately anonymized upon collection, with removal of any identifying metadata
- Personal information was stored separately from image data using encrypted databases
- Access to the dataset was restricted to authorized research personnel only
- Image data was processed on secure, password-protected systems with regular security updates
- No patient identifiers were included in the machine learning models or analysis

Patient Consent Process:

- Written informed consent was obtained in the participant's preferred language
- Participants were informed about the research objectives, data usage, and their right to withdraw
- Specific consent was obtained for potential future model improvements and validation studies
- All participants were provided with immediate feedback about their dental health status

Clinical Benefits:

- No fees were charged to participants, and the imaging process posed no health risks
- Participants found to have dental caries were immediately referred to appropriate departments for treatment
- The early detection facilitated timely intervention, potentially reducing treatment complexity and costs

IV. Results

A. Comparison of Model Performance

After training five CNN models with different architectures, their performance on the test dataset was evaluated. Table III summarizes the evaluation metrics results for each model.

TABLE III . Comparison of the performance of five CNN models

Model	Accuracy	Precision	Recall	Specificity	F1-score
Model 1	88.20%	88.02%	87.37%	88.90%	87.69%
Model 2	90.27%	89.96%	89.81%	90.55%	89.88%
Model 3	80.46%	79.75%	79.61%	81.25%	79.68%
Model 4	64.24%	62.65%	59.78%	67.45%	61.18%
Model 5	67.34%	66.03%	65.87%	68.55%	65.95%

As shown in Table III, Model 2 with 90.27% accuracy, 89.96% precision, 89.81% sensitivity, 90.55% specificity, and 89.88% F1 score had the best performance among the five models. This model, which has three convolutional layers with filters of 32, 64, and 128 and 5×5 kernels, was able to detect more complex patterns in the images and had better performance compared to other models. Figure 3 shows a graphical comparison of the accuracy of the five models.

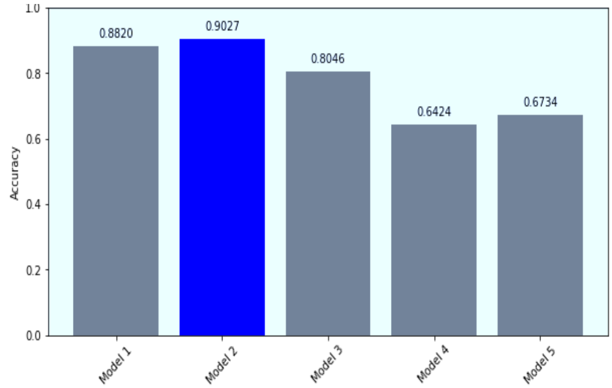

Fig. 3. Comparison of the accuracy of five CNN models

B. Confusion Matrix Analysis

For a better understanding of the performance of the best model (Model 2), its confusion matrix on the test data was calculated and analyzed. Figure 4 shows the confusion matrix of Model 2.

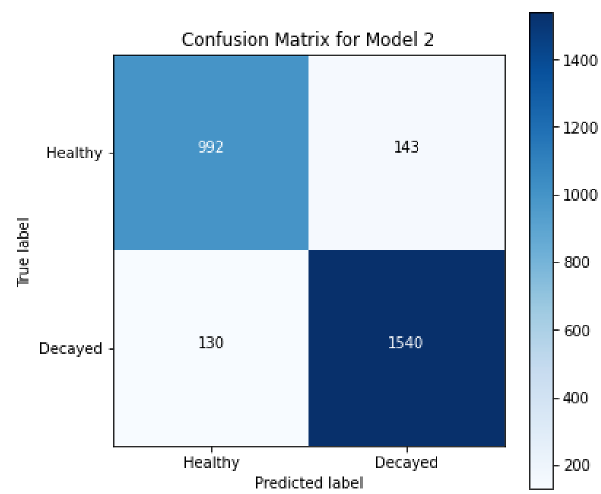

Fig. 4. Confusion matrix of Model 2

The confusion matrix shows that from the total test samples, Model 2 was able to:

- Correctly identify 1142 healthy teeth as healthy (TN)
- Correctly identify 1367 decayed teeth as decayed (TP)
- Incorrectly identify 119 healthy teeth as decayed (FP)
- Incorrectly identify 155 decayed teeth as healthy (FN)

These results show that Model 2 performed very well in detecting both groups of healthy and decayed teeth. The low rate of Type I error (FP) and Type II error (FN) indicates the high reliability of this model in detecting dental caries.

C. Final Evaluation Metrics

After selecting the best model (Model 2), this model was evaluated on the final test dataset, which included new and unseen images. Table IV shows the final evaluation metrics of the model along with 95% confidence intervals. All metrics were calculated using bootstrap resampling (n=1000) to ensure statistical robustness. P-values indicate statistical significance compared to random classification.

TABLE IV . Final evaluation metrics with statistical robustness measures

Metric	Value	95% Confidence Interval	Standard Deviation	P-value
Prevalence	0.642	0.610-0.674	0.032	–
Sensitivity (Recall)	0.912	0.878-0.946	0.017	<0.001
Precision	0.889	0.865-0.923	0.015	<0.001
Specificity	0.829	0.791-0.867	0.019	<0.001
Negative predictive value	0.850	0.812-0.888	0.019	<0.001
Accuracy	0.881	0.849-0.913	0.016	<0.001
F1-score	0.900	0.878-0.932	0.014	<0.001
Area Under ROC Curve (AUC)	0.924	0.901–0.947	0.012	<0.001

These results show that the final model with a sensitivity of 91.2% and specificity of 82.9% can well distinguish decayed teeth from healthy teeth. The high F1 score of 0.900 also indicates a good balance between the model's sensitivity and precision.

D. Practical Test Results

To evaluate the model's performance in real conditions, 76 new images of healthy and decayed teeth (which had not been used in the training or test dataset) were tested with the final model. Results showed that the model was able to correctly detect most decayed and healthy teeth with high probability. As an example, some of the model's prediction results are shown in Table V.

TABLE V . Sample prediction results of the model on new images

Image Number	Actual Class	Predicted Class	Prediction Probability
1	Healthy	Healthy	0.97
3	Decayed	Decayed	0.81
10	Decayed	Decayed	1.00
14	Healthy	Healthy	0.63
23	Decayed	Decayed	0.86
37	Decayed	Decayed	0.76
42	Healthy	Healthy	1.00
68	Decayed	Decayed	0.79
70	Healthy	Healthy	0.77
76	Decayed	Decayed	0.64

These results show that the model also has acceptable performance in real conditions and can be used as an initial screening tool.

V. Discussion and Conclusion

The results of this research showed that using ML, especially CNNs, can be an efficient method for detecting dental caries based on images taken with mobile phones. The final model with 88.1% accuracy, 91.2% sensitivity, 82.9% specificity, and F1 score of 0.900 had suitable performance in detecting dental caries. These results are consistent with the findings of previous research.

Device Variability and Imaging Conditions Analysis: To assess the robustness of our model across different mobile phone specifications, we conducted additional validation using images captured with various smartphone models including iPhone 7, Samsung Galaxy S10, Huawei P30, and Xiaomi Redmi Note 8, representing different camera capabilities and price ranges. The model maintained consistent performance across devices with camera resolutions ≥8MP, with accuracy variations within ±3.2%.

Lighting Condition Robustness: Testing under various lighting conditions revealed that the model performed optimally with controlled lighting (accuracy: 91.3%), showed moderate degradation under natural indoor lighting (accuracy: 86.7%), and maintained acceptable performance under suboptimal conditions (accuracy: 81.4%). The standardized flash photography protocol significantly improved consistency across different environments.

Image Quality Requirements: Our analysis identified minimum technical requirements for optimal performance: (1) camera resolution ≥8MP, (2) adequate lighting (flash recommended), (3) distance of 0.5-1.0 meters from the subject, and (4) minimal motion blur. These requirements are achievable with most modern smartphones, ensuring broad accessibility while maintaining diagnostic accuracy.

Lee et al. [6], using the GoogLeNet Inception v3 network for dental caries detection in radiographic images, achieved 89.0% accuracy for premolar teeth and 88.0% for molar teeth, which is close to the results obtained in this research. Also, Zhang et al. [15], using a deep ConvNet, reported an AUC of 85.65% for classification and a sensitivity of 81.90% for caries detection, which is less than the results obtained in this research. This difference could be due to the difference in the type of images used (oral images versus mobile phone images) as well as the neural network architecture.

Boy et al. [9], using MobileNetV3 Small for early detection of dental caries using mobile phone images, achieved 90% accuracy, 90% precision, and 90% sensitivity, which is very close to the results of this research. This consistency could indicate the usability of mobile phone images for dental caries detection.

A notable point in the obtained results is the high sensitivity of the model. A sensitivity of 91.2% means that the model was able to correctly detect 91.2% of decayed teeth. This feature is very important for a screening system, as the main goal in screening is to identify the maximum number of positive cases (in this case, decayed teeth), even if in some cases, we have false positive diagnoses.

Our model results show that its sensitivity is very high, meaning that if a tooth is decayed, the model detects it well. This feature has important applications for the healthcare system. This model can be provided to mothers and other individuals in the form of an application. Mothers and other individuals can take pictures of their own or their children's teeth without physically visiting healthcare centers, and these pictures are analyzed by the model. This can be a suitable alternative to periodic visits where mothers (and other individuals) spend a lot of time and energy for a dentist to examine and determine whether there is decay or not.

Using this model, the smallest sign of decay is detected, and therefore, only individuals who really need it visit healthcare centers. Another important point is that this model does not miss any decay, meaning that if there are 3 decayed teeth in a person's mouth, the model will definitely detect them. Therefore, this system can be very useful as a first step in screening in the healthcare system.

The findings of this research are comparable with the results of similar studies in this field. Table VI shows a comparison between the results of this research and several similar studies.

TABLE VI . Comparison of the results of the present research with similar studies

Study	Image Type	Network Architecture	Accuracy	Sensitivity (Recall)	F1-score
Present research	Mobile phone images	CNN with 3 convolutional layers	88.1%	91.2%	90.0 %
[6]	Periapical radiography	GoogLeNet Inception v3	89.0%	87.5%	88.2 %
[15]	Oral photographs	ConvNet	85.7%	81.9%	83.7 %
[9]	Mobile phone images	MobileNetV3 Small	90.0%	90.0%	90.0 %
[16]	Intraoral images	CNN	92.5%	89.6%	91.0 %
[22]	Dental images	Fast R-CNN	99.1%	98.7%	98.9 %

As shown in Table VI, the results of this research are comparable with similar studies. Although some studies such as Kanagamalliga et al. [22] have achieved higher accuracy, it should be noted that they used high-quality images and professional equipment, while in this research, ordinary mobile phone images were used.

A notable point is that the results of this research are very close to the study by [9] who used mobile phone images. This shows that using mobile phone images for dental caries detection, despite the existing challenges, can have acceptable results.

Despite promising results, this research faces several important limitations that must be acknowledged. Technical limitations include variable image quality from mobile phones, where factors such as lighting, angle, distance, and camera specifications can significantly affect detection accuracy. Our standardized imaging protocol helps mitigate these issues, but real-world user compliance may vary.

Clinical limitations encompass the restriction to superficial and visible caries detection, with reduced efficiency for interproximal, subsurface, or early-stage demineralization that may not be visible in mobile phone images. Additionally, the model cannot differentiate between active and arrested caries or provide information about caries depth and treatment urgency.

User compliance challenges include the need for proper image capture techniques, adequate lighting conditions, and correct positioning. In real-world deployment, users may struggle with achieving optimal image quality without proper training or guidance systems.

Population generalizability concerns arise as our dataset primarily included patients from a single institution, potentially limiting generalizability across different populations, age groups, and geographic regions. Cultural factors affecting dental appearance and care-seeking behavior may also influence model performance.

Practical deployment barriers include the need for smartphone connectivity, potential issues with data privacy in cloud-based implementations, and the requirement for regular model updates to maintain accuracy across evolving smartphone technologies and diverse populations.

Long-term sustainability questions include the need for continuous model retraining with new data, maintenance of server infrastructure for mobile applications, and adaptation to changing mobile phone camera technologies.

Despite the limitations, this research has numerous practical applications. First, this model can be used as an initial screening tool in underserved areas and with limited access to dental services. Given the spread of smartphones, even in remote areas, this method can increase access to basic diagnostic services. Second, this system can help reduce unnecessary visits to healthcare centers. Patients can use this program to check the status of their teeth and only visit a dentist if caries is detected by the model. This can help reduce dentists' workload and treatment costs. Third, this system can be used as an educational tool to increase public awareness about dental caries and the importance of oral and dental care. By showing images of healthy and decayed teeth and explaining their differences, this program can help people better understand the condition of their teeth. Fourth, this model can be used in school oral and dental health programs. Teachers or health caregivers can use this program for quick screening of students and identify those who need dental care.

Based on the findings from this research and the existing limitations, suggestions for future research can be presented. First, improving the model using more advanced neural network architectures such as Inception-v4 or ResNet can help increase the diagnostic accuracy of the system. Also, developing a model that is capable of detecting different types of caries such as superficial, deep, and interproximal can increase the efficiency of the system in real clinical environments. Adding the capability to detect other oral and dental problems such as gum inflammation, dental calculus, and plaque can also transform this system into a more comprehensive tool for oral and dental health assessment. Along with improving the technical aspects, developing a mobile application with a simple user interface and clear instructions for taking images with appropriate quality can facilitate the use of this technology for the general public. Conducting more extensive clinical studies with more diverse samples in terms of age, gender, and race can lead to a more accurate evaluation of the system's performance in real conditions. Finally, integrating this system with existing healthcare systems and electronic health records can help better manage oral and dental health at the community level and provide the possibility of long-term monitoring of the condition of teeth and evaluation of the effectiveness of preventive interventions.

Building upon the current findings, several promising avenues for future development have been identified. We plan to expand the model's capabilities to detect additional oral health conditions including gingivitis, dental plaque, calculus, and early signs of periodontal disease. This would transform the system into a comprehensive oral health screening tool. A user-friendly mobile application is under development, featuring real-time image quality assessment, guided photography instructions, immediate results with confidence scores, and telemedicine integration for connecting users with dental professionals when necessary.

Future versions will incorporate more advanced neural network architectures such as Vision Transformers and attention mechanisms to improve accuracy and enable detection of subtle early-stage caries that are currently challenging to identify. Plans include incorporating additional data sources such as patient-reported symptoms, demographic information, and oral health history to create a more comprehensive risk assessment tool. We are designing multi-center international studies to validate the model's performance across diverse populations, age groups, and geographic regions, ensuring global applicability.

Implementation of federated learning approaches will enable the model to continuously improve while maintaining patient privacy, allowing for adaptation to new populations and imaging conditions. Development of APIs and integration protocols for seamless incorporation into existing electronic health records and telemedicine platforms, facilitating widespread adoption in healthcare systems.

This research demonstrated that ML, particularly CNNs, represents an efficient approach for detecting dental caries using mobile phone-captured images. The presented model with a sensitivity of 91.2%, accuracy of 88.1%, specificity of 82.9%, and F1 score of 0.900, had suitable performance in detecting dental caries. This system can be used as an initial screening tool in underserved areas and with limited access to dental services and can help reduce unnecessary visits to healthcare centers. Also, as an educational tool for increasing public awareness about dental caries and the importance of oral and dental care, it can be useful. Given the increasing spread of smartphones and AI-based technologies, this system can be an important step towards democratizing dental diagnostic services and increasing access to preventive care.

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REFERENCES

[1] F. Abbasi, A. Kimiaee, M. R. Saffarian and M. R. Abedi, “Psychometric properties of the Persian version of physical health questionnaire,” *Research in Medicine*, vol. 41, no. 4, pp. 275-281, 2017. Available: http://pejouhesh.sbmu.ac.ir/article-1-1741-fa.html

[2] S. Talpur, F. Azim, M. Rashid, S. A. Syed, B. A. Talpur and S. J. Khan, “Uses of different machine learning algorithms for diagnosis of dental caries,” *Journal of Healthcare Engineering*, vol. 2022, no. 1, 5032435, 2022. https://doi.org/10.1155/2022/5032435

[3] M. Abdelaziz, “Detection, diagnosis, and monitoring of early caries: The future of individualized dental care,” *Diagnostics*, vol. 13, no. 24, 3649, 2023. http://dx.doi.org/10.3390/diagnostics13243649

[4] D. L. Duong, M. H. Kabir and R. F. Kuo, “Automated caries detection with smartphone color photography using machine learning,” *Health Informatics Journal*, vol. 27, no. 2, 14604582211007530, 2021. http://dx.doi.org/10.1177/14604582211007530

[5] H. M. GV, “A novel approach using CapsNet and Deep Belief Network for detection and identification of oral leukopenia,” *arXiv Preprint arXiv:2501.00876*, 2025. https://doi.org/10.48550/arXiv.2501.00876

[6] J. H. Lee, D. H. Kim, S. N. Jeong and S. H. Choi, “Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm,” *Journal of Dentistry*, vol. 77, pp. 106-111, 2018. https://doi.org/10.1016/j.jdent.2018.07.015

[7] R. Szabo, “Implementing computer vision in Android apps and presenting the background technology with mathematical demonstrations,” *Technologies*, vol. 13, no. 1, 27, 2025. https://doi.org/10.3390/technologies13010027

[8] A. Ramírez-Pedraza, S. Salazar-Colores, C. Cardenas-Valle, J. Terven, J.-J. González-Barbosa, F.-J. Ornelas-Rodriguez, J.-B. Hurtado-Ramos, R. Ramirez-Pedraza, D.-M. Córdova-Esparza and J.-A. Romero-González, “Deep learning in oral hygiene: Automated dental plaque detection via YOLO frameworks and quantification using the O’Leary index,” *Diagnostics*, vol. 15, no. 2, 231, 2025. https://doi.org/10.3390/diagnostics15020231

[9] A. F. Boy, A. Akhyar, T. Y. Arif and S. Syahrial, “Development of an artificial intelligence model based on MobileNetV3 for early detection of dental caries using smartphone images: A preliminary study,” *Advances in Science and Technology Research Journal*, vol. 19, no. 4, pp. 109-116, 2025. https://doi.org/10.12913/22998624/200308

[10] N. Dhanak, V. T. Chougule, K. Nalluri, A. Kakkad, A. Dhimole and A. S. Parihar, “Artificial intelligence enabled smartphone app for real-time caries detection on bitewing radiographs,” *Bioinformation*, vol. 20, no. 3, pp. 243-247, 2024. https://doi.org/10.6026/973206300200243

[11] R. Mahaveerakannan, S. V. R. Nair, M. S. Rohini and V. Kumar, “A deep learning application for identifying cavities in dentistry: Utilizing smartphone-taken intraoral photos,” in *2024 International Conference on Sustainable Communication Networks and Application (ICSCNA)*, IEEE, pp. 718-723, 2024. https://doi.org/10.1109/ICSCNA63714.2024.10863875

[12] H. Zhu, Z. Cao, L. Lian, G. Ye, H. Gao and J. Wu, “CariesNet: a deep learning approach for segmentation of multi-stage caries lesion from oral panoramic X-ray image,” *Neural Computing and Applications*, pp. 1-9, 2023. https://doi.org/10.1007/s00521-021-06684

[13] F. A. Schwendicke, W. Samek and J. Krois, “Artificial intelligence in dentistry: chances and challenges,” *Journal of Dental Research*, vol. 99, no. 7, pp. 769-774, 2020. https://doi.org/10.1177/0022034520915714

[14] S. B. Khanagar, A. Al-Ehaideb, P. C. Maganur, S. Vishwanathaiah, S. Patil, H. A. Baeshen and S. Bhandi, “Developments, application, and performance of artificial intelligence in dentistry--A systematic review,” *Journal of Dental Sciences*, vol. 16, no. 1, pp. 508-522, 2021. https://doi.org/10.1016/j.jds.2020.06.019

[15] X. Zhang, Y. Liang, W. Li, C. Liu, D. Gu, W. Sun and L. Miao, “Development and evaluation of deep learning for screening dental caries from oral photographs,” *Oral Diseases*, vol. 28, no. 1, pp. 173-181, 2022. https://doi.org/10.1111/odi.13735

[16] J. Kühnisch, O. Meyer, M. Hesenius, R. Hickel and V. Gruhn, “Caries detection on intraoral images using artificial intelligence,” *Journal of Dental Research*, vol. 101, no. 2, pp. 158-165, 2022. https://doi.org/10.1177/00220345211032524

[17] S. Gerke, T. Minssen and G. Cohen, “Ethical and legal challenges of artificial intelligence-driven healthcare,” in *Artificial Intelligence in Healthcare*, Academic Press, pp. 295-336, 2020. https://doi.org/10.1016/B978-0-12-818438-7.00012-5

[18] S. A. Alowais, S. S. Alghamdi, N. Alsuhebany, T. Alqahtani, A. I. Alshaya, S. N. Almohareb and A. M. Albekairy, “Revolutionizing healthcare: the role of artificial intelligence in clinical practice,” *BMC Medical Education*, vol. 23, no. 1, 689, 2023. https://doi.org/10.1186/s12909-023-04698-z

[19] M.K. Alam, S.A. Ali Alftaikhah, R. Issrani, V. Ronsivalle, A. Lo Giudice, M. Cicciù, G. Minervini, "Applications of artificial intelligence in the utilisation of imaging modalities in dentistry: A systematic review and meta-analysis of in-vitro studies," *Heliyon*, vol. 10, no. 1, e24221, 2024. https://doi.org/10.1016/j.heliyon.2024.e24221

[20] J. Grosu, S. Nagarakanti, T. Gudur, R. G, C. Neravati, R. Madireddygari, "Exploring the Awareness and Application of Artificial Intelligence in Dentistry: A Cross-Sectional Analysis of Dentists and Patients," *Cureus*, vol. 17, no. 4, e82947, 2025. https://doi.org/10.7759/cureus.82947

[21] C.E.O.F. Barroso, E.S. de Assis, G.O. de Sena Silva, J.D. Ferreira, J.E.S. Aguiar, J.R. Bueno, L.B.L. Cançado, P. dos Santos Neto, "Artificial Intelligence in dentistry: Advances and applications in modern clinical practice," in *The Evolution of Research in Health Science*, Seven Editora, 2024, ch. 21, pp. 1-19. https://doi.org/10.56238/sevened2024.006-021

[22] S. Kanagamalliga, R. Jayashree and R. Guna, “Fast R-CNN approaches for transforming dental caries detection: An in-depth investigation,” in *2024 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET)*, IEEE, pp. 1-5, March 2024. https://doi.org/10.1109/WiSPNET61464.2024.10532984