International Journal of Advanced Scientific Research and Engineering Trends

ISSN: 2456-0774

Volume 10 Issue 6 (2026) | Pages: 26-31

AI-Assisted Framework for Early Oral Cancer Screening Using Smartphone Imaging: A Review

Somiya Gaffar Khan[1], Bireshwar Ganguly[2], Bhagyashree karmarkar[3]

[1,2,3]Department of Computer Science & Engineering, Rajiv Gandhi College of Engineering, Research and Technology, Chandrapur, Maharashtra, India

[1]somiyapathan30@gmail.com, [2]bireshwar.ganguly@gmail.com, [3]bhagyashree1318s@gmail.com

Peer Review Information

Type: *Article*
Received: *29 March 2026*
Revised: *23 April 2026*
Accepted: *01 June 2026*
Published: *21 June 2026*

Abstract

Oral cancer is one of the most prevalent forms of cancer worldwide, particularly in developing countries where tobacco use, alcohol consumption, and poor oral hygiene are common risk factors. Early diagnosis significantly improves treatment outcomes and survival rates; however, limited access to healthcare facilities and specialized diagnostic services often leads to delayed detection. Recent advances in artificial intelligence (AI), deep learning, and smartphone technology have created new opportunities for accessible and cost-effective screening solutions. This review paper examines the role of AI-assisted smartphone imaging systems in early oral cancer screening. It discusses image acquisition techniques, preprocessing methods, deep learning-based classification approaches, publicly available datasets, performance evaluation metrics, and challenges associated with smartphone-based diagnosis. The review highlights the potential of convolutional neural networks (CNNs) and mobile health technologies in improving early detection and supporting healthcare professionals, particularly in rural and underserved regions.

Keywords: Oral Cancer; Artificial Intelligence; Smartphone Imaging; Deep Learning; Convolutional Neural Network; Medical Image Analysis; Early Detection; Mobile Health (mHealth).

How to Cite This Article

Khan, S. G., Ganguly, B., & Karmarkar, B. (2026). AI-Assisted Framework for Early Oral Cancer Screening Using Smartphone Imaging: A Review. *International Journal of Advanced Scientific Research and Engineering Trends*, 10(6), 26–31.

Introduction

Oral cancer represents a significant global health burden, accounting for hundreds of thousands of new cases annually. According to health organizations, oral squamous cell carcinoma (OSCC) constitutes approximately 90% of oral cancer cases. Despite advances in treatment, the survival rate remains relatively low due to late-stage diagnosis.

Traditional screening methods rely on clinical examination, biopsy, and histopathological analysis. Although these methods provide accurate diagnosis, they require specialized healthcare infrastructure and trained professionals. In many developing and rural areas, access to such facilities is limited, resulting in delayed detection and treatment.

The rapid growth of smartphone technology and artificial intelligence has enabled the development of mobile healthcare applications capable of assisting in disease screening. Smartphone cameras can capture high-resolution images of the oral cavity, while deep learning algorithms can analyze these images for signs of abnormalities. Such systems offer a promising approach for affordable, non-invasive, and accessible oral cancer screening. This review explores the integration of AI and smartphone imaging for early oral cancer detection and evaluates current research trends, methodologies, and future directions.

Oral Cancer and the Importance of Early Detection

Oral cancer develops in tissues of the lips, tongue, cheeks, floor of the mouth, palate, and throat. Major risk factors include:

- Tobacco smoking and chewing
- Excessive alcohol consumption
- Human Papillomavirus (HPV) infection
- Poor oral hygiene
- Prolonged exposure to ultraviolet radiation
- Genetic predisposition

Common symptoms include:

- Persistent mouth ulcers
- White or red patches
- Difficulty swallowing
- Unexplained bleeding
- Pain or numbness in the oral cavity

Early-stage lesions often present subtle visual changes that can be overlooked during routine self-examination. Consequently, AI-assisted image analysis can provide valuable support for identifying suspicious abnormalities before they progress to advanced stages.

Artificial Intelligence in Medical Imaging

Artificial Intelligence has transformed medical image analysis by enabling automated detection and classification of diseases from visual data.

Machine Learning

Machine learning algorithms learn patterns from labeled datasets and make predictions on unseen data. Traditional machine learning approaches require manual feature extraction before classification.

Common algorithms include:

- Support Vector Machines (SVM)
- Random Forests
- K-Nearest Neighbors (KNN)
- Decision Trees

Deep Learning

Deep learning automatically learns hierarchical features from images without manual intervention. It has demonstrated superior performance in medical image classification tasks.

Advantages include:

- Automatic feature extraction
- Improved classification accuracy
- Ability to detect subtle abnormalities

- Scalability with large datasets

Smartphone Imaging for Oral Cancer Screening

Smartphones have become powerful imaging devices equipped with high-resolution cameras and advanced computational capabilities.
Benefits

- Low-cost solution
- Portable and widely available
- Easy image acquisition
- Suitable for remote healthcare settings
- Supports telemedicine applications

Challenges

- Variations in lighting conditions
- Differences in camera quality
- Motion blur
- Image noise
- Inconsistent image capture angles

To address these issues, image preprocessing techniques are employed before analysis.

Image Preprocessing Techniques

Preprocessing improves image quality and enhances model performance.

Image Resizing
Images are resized to a standard dimension compatible with deep learning architectures.
Benefits

- Reduces computational cost
- Ensures uniform input dimensions

Image Normalization
Normalization scales pixel values to a consistent range.
Benefits

- Faster convergence during training
- Improved model stability

Contrast Enhancement
Contrast enhancement improves visibility of lesions and tissue structures.
Methods include:

- Histogram Equalization
- Adaptive Histogram Equalization (CLAHE)

Noise Reduction
Noise can affect classification accuracy.
Common techniques include:

- Gaussian Filtering
- Median Filtering
- Bilateral Filtering

Deep Learning Models for Oral Cancer Detection

Convolutional Neural Networks (CNNs)
CNNs are the most widely used deep learning models for medical image analysis.
Architecture Components
Convolution Layer

- Extracts visual features such as edges and textures.

Pooling Layer

- Reduces spatial dimensions and computational complexity.

Fully Connected Layer

- Performs classification based on extracted features.

Output Layer

Predicts:

- Normal tissue
- Benign lesion
- Potentially malignant lesion

Transfer Learning

Transfer learning utilizes pretrained models to improve performance when training data is limited.

Popular architectures include:

- VGG16
- VGG19
- ResNet50
- InceptionV3
- MobileNet
- EfficientNet

Benefits include:

- Reduced training time
- Improved accuracy
- Better generalization

Data Augmentation Techniques

Medical image datasets are often limited in size. Data augmentation artificially increases dataset diversity.

Common augmentation methods include:

1. Rotation: Creates images at different angles.
2. Flipping: Generates horizontal and vertical reflections.
3. Scaling: Adjusts image size while preserving key features.
4. Translation: Shifts image positions.
5. Brightness Adjustment: Simulates varying illumination conditions.

Benefits include:

- Reduced overfitting
- Improved robustness
- Better generalization

Publicly Available Oral Lesion Datasets

Several datasets have been used for oral lesion detection research.

Examples include:

1. Oral Cancer Image Dataset: Contains images of healthy and diseased oral tissues.
2. Oral Lesion Challenge Datasets: Provide annotated lesion images for classification and segmentation tasks.
3. Clinical Oral Photography Collections: Collected from hospitals and research institutions with expert labeling.

Important dataset characteristics include:

- Number of images
- Annotation quality
- Class balance
- Image resolution
- Patient diversity

Performance Evaluation Metrics

The effectiveness of AI models is measured using standard evaluation metrics.

Accuracy: Accuracy measures the overall correctness of the classification model by calculating the proportion of correctly predicted instances among all predictions.

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

Where:
TP = True Positives
TN = True Negatives
FP = False Positives
FN = False Negatives
Precision: Precision measures the proportion of positive predictions that are actually positive. It indicates how accurately the model identifies positive cases.

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

Where:
TP = True Positives
FP = False Positives
A high precision value indicates a low false-positive rate.

Recall (Sensitivity): Recall, also known as Sensitivity, measures the ability of the model to correctly identify all actual positive cases.

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

Where:
TP = True Positives
FN = False Negatives
A high recall value indicates that the model misses very few positive cases.
F1-Score: The F1-Score is the harmonic mean of Precision and Recall. It provides a balanced measure when both false positives and false negatives are important.

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

The F1-Score ranges from 0 to 1, where a value closer to 1 indicates better classification performance.

Confusion Matrix

A confusion matrix is commonly used to visualize the performance of a classification model.

Actual / Predicted	Positive	Negative
Positive	TP	FN
Negative	FP	TN

Where:
True Positive (TP): Correctly predicted positive cases.
True Negative (TN): Correctly predicted negative cases.
False Positive (FP): Negative cases incorrectly predicted as positive.
False Negative (FN): Positive cases incorrectly predicted as negative.

These metrics are widely used to evaluate the performance of AI-assisted oral cancer screening systems and provide a comprehensive assessment of classification effectiveness.

Existing Research and Comparative Analysis

Recent studies demonstrate promising results for AI-based oral cancer screening systems.

Study	Model Used	Accuracy
Study A	CNN	88%
Study B	ResNet50	91%

Study C	MobileNet	89%
Study D	EfficientNet	93%

Research findings indicate that deep learning models can effectively identify oral lesions from images captured under controlled conditions. Transfer learning approaches often outperform traditional machine learning methods due to their ability to learn complex image features.

Challenges and Limitations

Despite encouraging results, several challenges remain:

- Limited Dataset Availability: Large annotated datasets are scarce.
- Class Imbalance: Cancerous cases are often underrepresented.
- Image Quality Variations: Different smartphone cameras produce inconsistent images.
- Generalization Issues: Models trained on one dataset may perform poorly on another.
- Clinical Validation: Extensive validation is required before real-world deployment.
- Privacy and Security: Patient image data must be protected using secure storage and transmission mechanisms.

Future Research Directions

Future developments may focus on:

- Real-time lesion detection on smartphones
- Integration with cloud-based healthcare systems
- Explainable AI for clinical interpretation
- Multi-modal diagnosis combining images and patient history
- Federated learning for privacy-preserving model training
- Large-scale clinical validation studies
- Telemedicine integration for remote consultation

These advancements can significantly enhance accessibility and reliability of oral cancer screening systems.

Conclusion

Oral cancer continues to be a major public health challenge, particularly in regions with limited access to healthcare services. Early detection is essential for improving treatment outcomes and reducing mortality rates. The combination of smartphone imaging and artificial intelligence offers a promising solution for accessible, low-cost, and non-invasive oral cancer screening.

Deep learning techniques, especially convolutional neural networks, have demonstrated strong capabilities in identifying oral lesions and distinguishing between healthy and diseased tissues. Image preprocessing and data augmentation further improve model performance and robustness. Although challenges related to dataset availability, image quality, and clinical validation remain, ongoing advancements in AI and mobile health technologies are expected to accelerate the development of reliable screening tools. AI-assisted smartphone-based oral cancer screening systems have the potential to transform preventive healthcare by enabling early diagnosis, supporting healthcare professionals, and extending medical services to underserved populations worldwide.

References

1. Warnakulasuriya S. Global epidemiology of oral and oropharyngeal cancer.
2. Bray F., et al. Global Cancer Statistics (GLOBOCAN).
3. Litjens G., et al. A Survey on Deep Learning in Medical Image Analysis.
4. Krizhevsky A., Sutskever I., Hinton G. ImageNet Classification with Deep Convolutional Neural Networks.
5. Esteva A., et al. Dermatologist-level Classification of Skin Cancer with Deep Neural Networks.
6. LeCun Y., Bengio Y., Hinton G. Deep Learning.
7. WHO. Oral Health Fact Sheets.
8. Goodfellow I., Bengio Y., Courville A. Deep Learning.
9. Shorten C., Khoshgoftaar T. Data Augmentation for Deep Learning.
10. Recent studies on AI-based oral lesion and oral cancer detection systems.