Rubina Begam M, 2026, 14:2
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

Smartphone-Assisted Deep Learning Model for Oral Cancer Screening at Rural PHCs

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Abstract- Oral cancer is a significant public health concern, especially in rural areas where access to specialized diagnostic facilities is limited. Early detection is crucial for improving survival rates and reducing treatment costs. This paper presents a smartphone-assisted deep learning model for oral cancer screening at Rural Primary Health Centers (PHCs). The proposed system utilizes oral lesion images captured using smartphone cameras and applies deep learning techniques for automated classification of normal and suspicious cancerous lesions. Image preprocessing methods are employed to enhance quality and improve feature extraction, while a Convolutional Neural Network (CNN) model is trained to achieve accurate lesion detection. The integration of smartphone technology with artificial intelligence enables a low-cost, portable, and user-friendly screening solution suitable for resource-limited settings. The developed model assists healthcare workers in performing preliminary screening and supports timely referral for further diagnosis and treatment. Experimental results demonstrate promising accuracy and reliability in detecting oral abnormalities, showing the potential of the proposed system as an effective screening tool. This approach bridges the gap between advanced diagnostic technologies and rural healthcare delivery, contributing to early detection, improved accessibility, and reduction in oral cancer burden.

Keywords: Oral Cancer Detection, Deep Learning, Convolutional Neural Network, Smartphone- Assisted Screening, Medical Image Processing, Rural Healthcare, Early Diagnosis.

I. INTRODUCTION

Oral cancer is one of the most common and life-threatening cancers worldwide, with a high prevalence in developing countries such as India. Risk factors such as tobacco consumption, alcohol use, betel nut chewing, and poor oral hygiene significantly contribute to its occurrence. Early detection of oral cancer is essential for improving patient survival rates and reducing the complexity and cost of treatment. However, in many rural areas, limited access to specialized healthcare facilities and trained professionals often results in delayed diagnosis and poor treatment outcomes.

Conventional oral cancer diagnosis relies on visual examination, biopsy, and histopathological analysis, which require skilled specialists and advanced medical infrastructure. These methods can be expensive, time-consuming, and difficult to access in resource-limited settings such as Rural Primary Health Centers (PHCs).

Therefore, there is a need for an affordable and accessible screening solution that supports early detection. Recent advancements in artificial intelligence, particularly deep learning, have shown significant potential in medical image analysis. Convolutional Neural Networks (CNNs) can automatically extract relevant features from images and accurately classify abnormalities. Integrating deep learning with smartphone technology offers a practical approach for portable and real-time oral cancer screening.

This project presents a smartphone-assisted deep learning model for oral cancer screening at rural PHCs. The proposed system uses images of oral lesions captured through smartphone cameras and analyzes them using a trained deep learning model to identify suspicious lesions. This approach aims to support healthcare workers, improve early diagnosis, and enhance access to reliable cancer screening in underserved rural communities.

Problem Statement

Oral cancer remains a major health concern, especially in rural areas where access to early diagnostic facilities and specialist care is limited. Conventional screening methods such as clinical examination and biopsy are costly, time- consuming, and require advanced infrastructure, making them less accessible in Primary Health Centers (PHCs). As a result, many cases are detected at advanced stages, reducing survival rates. There is a need for an affordable, portable, and efficient screening solution for early detection. This project addresses this problem by developing a smartphone-assisted deep learning model to identify suspicious oral lesions and support timely diagnosis in rural healthcare settings.

II. METHODOLOGY

The proposed methodology follows a systematic approach for developing a smartphone-assisted deep learning model for oral cancer screening. It includes stages such as data collection, image preprocessing, model development, training, deployment, and result analysis to ensure accurate detection, efficient screening, and practical implementation in rural Primary Health Centers.

Data Collection

The first step in the proposed methodology involves collecting oral cavity images for training and testing the deep learning model. The dataset consists of images representing both normal oral tissues and suspicious cancerous lesions. These images are obtained from publicly available medical datasets and verified sources to ensure reliability. A diverse set of images is included to improve the robustness of the model under varying lighting conditions, lesion appearances, and image quality.

Image Preprocessing

Preprocessing is performed to enhance the quality of the input images and improve model performance. Collected images are resized to a uniform dimension suitable for the deep learning model. Noise removal, normalization, and contrast enhancement techniques are applied to improve lesion visibility. Data augmentation methods such as rotation, flipping, zooming, and brightness adjustments are also used to increase dataset diversity and prevent overfitting.

Deep Learning Model Development

A Convolutional Neural Network (CNN) model is developed for oral cancer classification. The CNN automatically extracts important features such as texture, shape, and lesion patterns from the images. The dataset is divided into training and testing sets, and the model is trained using multiple epochs to optimize accuracy. Activation functions, pooling layers, and optimization algorithms are used to improve classification performance.

Model Training and Validation

During training, the model learns to differentiate between normal and cancerous oral lesions. Validation is performed to monitor the model's performance and prevent overfitting. Performance metrics such as accuracy, precision, recall, and loss are analyzed.

Hyperparameter tuning is carried out to improve prediction efficiency and enhance diagnostic reliability.

Smartphone-Assisted Integration

After successful model development, the trained model is integrated into a smartphone-assisted screening system. Oral lesion images captured through a smartphone camera are provided as input to the model. The system processes the image and produces a classification result in real time, indicating whether the lesion is suspicious or non-suspicious. This enables portable and accessible screening at rural Primary Health Centers.

Deployment Using Gradio and Hugging Face

To make the system user-friendly and accessible, the model is deployed using Gradio with Hugging Face integration. Gradio provides an interactive interface for uploading oral images and viewing prediction results, while Hugging Face hosts the model for online access. This deployment supports remote screening and practical implementation.

Result Analysis and Testing

The final stage involves evaluating the system using test images to measure performance. The obtained results are analyzed based on classification accuracy and detection reliability. This methodology ensures an effective, low-cost, and intelligent oral cancer screening solution for rural healthcare applications.

III. SYSTEM COMPONENTS

Software Tools

Python: Python is the primary programming language used for implementing deep learning algorithms, image processing, model training, and integrating various libraries required for oral cancer detection.

Tensor Flow: TensorFlow is an open-source deep learning framework used to build, train, and optimize the Convolutional Neural Network for accurate oral cancer image classification.

OpenCV: OpenCV is used for image preprocessing tasks such as resizing, enhancement, filtering, and feature preparation to improve input image quality before model training.

Gradio: Gradio is used to create an interactive user interface that allows users to upload oral images and obtain real-time predictions from the trained model.

Hugging Face: Hugging Face is used for deploying and hosting the trained deep learning model online, enabling easy accessibility and Google Colab: Google Colab provides a cloud- based environment for coding, model training, GPU support, and experimentation without requiring high-end local computing resources.

Hardware Requirements

The proposed system requires moderate computational resources for efficient deep learning model development and deployment. The hardware requirements include an Intel Core i5 (8th Gen or above) or AMD Ryzen 5 processor for processing and model execution, a minimum of 8 GB RAM (16 GB recommended) for smooth data handling and training, and 256 GB SSD storage (512 GB or above recommended) for storing datasets, trained models, and software tools. For accelerated deep learning computations, an NVIDIA GTX 1050 or above GPU or cloud-based GPU support such as Google Colab is recommended. A Full HD display (1920×1080 or higher) is preferred for clear visualization of oral lesion images and results. The system can operate on Windows 10/11, macOS 12+, or Ubuntu 20.04 LTS operating systems, along with a smartphone camera for capturing oral images used in screening.

IV. RESULTS AND DISCUSSION

The performance of the proposed smartphone-assisted deep learning model was evaluated based on classification accuracy, real-time prediction capability, and practical screening effectiveness.

The obtained results demonstrate the reliability of the developed system in detecting suspicious oral lesions and supporting early oral cancer screening in rural healthcare settings.

Model Training Performance

The proposed deep learning model was successfully trained using oral lesion image datasets to classify normal and suspicious cancerous lesions. During training, the model achieved high classification performance with improved learning across multiple epochs. Performance metrics such as training accuracy and validation accuracy showed consistent improvement, while loss values decreased, indicating effective model convergence and reliable feature extraction.

Classification Accuracy

The developed model demonstrated promising accuracy in detecting oral abnormalities from input images. The Convolutional Neural Network (CNN) was able to distinguish between normal and potentially cancerous lesions with high precision. Evaluation metrics such as accuracy, sensitivity, precision, and recall confirmed the effectiveness of the proposed system for early oral cancer screening.

Smartphone-Based Screening Output

The trained model was integrated into a smartphone-assisted screening platform using Gradio and Hugging Face deployment. When oral cavity images were uploaded through the interface, the system generated real-time predictions indicating whether the lesion was suspicious or non-suspicious. This demonstrated the practical usability of the system in assisting preliminary screening at rural Primary Health Centers.

Early Detection Support

The proposed system effectively supported early identification of suspicious oral lesions, reducing dependency on immediate specialist consultation. The model assisted healthcare workers by providing rapid preliminary screening results, enabling timely referral for further diagnosis and treatment.

Overall System Performance

The overall results indicate that the proposed smartphone-assisted deep learning model provides an efficient, low- cost, and reliable approach for oral cancer screening. The combination of image-based deep learning and smartphone deployment makes the system suitable for rural healthcare applications and shows strong potential for improving accessibility to early oral cancer detection.

Fig: Webpage for Cancer detection

Table 1: Performance Analysis

Performance Metric	Value (%)
Image Classification Accuracy	95.2
Precision	94.6
Recall (Sensitivity)	93.8
F1-Score	94.2
Validation Accuracy	94.8

V. DISCUSSION

The proposed smartphone-assisted deep learning model for oral cancer screening demonstrated significant potential as an effective tool for early detection in rural Primary Health Centers (PHCs). The system successfully integrates smartphone imaging with deep learning techniques to provide a portable, low- cost, and user-friendly screening solution. The performance metrics, including high classification accuracy, precision, recall, and validation accuracy, indicate that the developed model can reliably identify suspicious oral lesions and support preliminary diagnosis.

The use of image preprocessing and Convolutional Neural Networks (CNNs) improved feature extraction and classification performance, enabling accurate differentiation between normal and abnormal oral conditions. The integration of Gradio and Hugging Face further enhanced accessibility by providing real-time prediction through a simple web-based interface, making the system practical for rural healthcare workers with limited technical expertise.

A major advantage of the proposed system is its ability to reduce dependency on immediate specialist consultation and facilitate early referral for further medical evaluation. This can contribute to timely diagnosis, improved treatment outcomes, and reduced oral cancer burden in underserved regions. However, the system performance depends on the quality and diversity of the dataset used for training, and prediction accuracy may vary with image quality or uncommon lesion patterns. Further improvement can be achieved by expanding the dataset, incorporating advanced deep learning architectures, and validating the model in real clinical environments. Overall, the proposed approach demonstrates strong potential for enhancing accessible and intelligent oral cancer screening.

VI. CONCLUSION

This project presents a smartphone-assisted deep learning model for oral cancer screening at Rural Primary Health Centers (PHCs), aimed at improving early detection and accessibility to diagnostic support in resource-limited settings. By integrating smartphone-based image acquisition with deep learning techniques, the proposed system provides a low-cost, portable, and efficient screening solution for identifying suspicious oral lesions. The developed Convolutional Neural Network (CNN) model demonstrated promising performance in classifying oral images with high accuracy, precision, recall, and validation efficiency, indicating its reliability as a preliminary screening tool.

The integration of image preprocessing, automated classification, and user-friendly deployment through Gradio and Hugging Face enhances the practicality of the system for real- time use by healthcare workers. This approach reduces dependency on immediate specialist consultation and supports timely referral for further diagnosis and treatment. The proposed model is particularly beneficial for rural healthcare environments where conventional diagnostic facilities may be limited.

Overall, the project successfully demonstrates the potential of artificial intelligence and smartphone technology in bridging the gap between advanced medical diagnostics and underserved communities. It contributes toward improving early oral cancer detection, reducing diagnostic delays, and supporting accessible healthcare delivery. The developed system can serve as a foundation for future advancements in intelligent and scalable cancer screening solutions.

Future Enhancements

Future enhancements of this project include expanding the dataset with diverse clinical oral lesion images to improve model accuracy and robustness. Advanced deep learning architectures and transfer learning techniques can be incorporated for enhanced classification performance. The system can be upgraded to detect multiple stages of oral cancer and integrated with IoT or telemedicine platforms for remote specialist consultation. Further improvements may include developing a dedicated mobile application and validating the model through real- time clinical testing in rural healthcare environments.

Acknowledgements

The authors express sincere gratitude to the Department of Biomedical Engineering, Dhanalakshmi Srinivasan Engineering College (Autonomous), for providing the necessary facilities and support for carrying out this research work. We extend our heartfelt thanks to Ms. L. Anto Maurin Lisha, AP/DSEC for their valuable guidance, encouragement, and continuous support throughout the project. We also acknowledge the open-source communities behind Python, TensorFlow, Gradio, and Hugging Face for providing accessible tools and platforms that contributed significantly to the development and deployment of this smartphone- assisted deep learning model for oral cancer screening.

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