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Mobile-Based AI Decision Support System For Early Oral Cancer Risk Screening

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Abstract
Oral cancer is a serious global public health concern, especially in developing nations where poor oral hygiene, alcohol intake, and tobacco use greatly raise the risk of disease development. Improving survival rates requires early detection, but traditional screening techniques frequently rely on clinical infrastructure and qualified specialists, which may not be available in remote or resource-constrained areas.This study suggests a mobile-based artificial intelligence decision support system that combines risk factor assessment and medical picture analysis for early oral cancer risk screening. While a structured questionnaire module assesses behavioral and clinical risk factors, the system uses a Convolutional Neural Network (CNN) to analyze intraoral pictures and detect worrisome lesions. Grad-CAM, an Explainable Artificial Intelligence (XAI) approach, is used to highlight important areas in the oral picture in order to visually explain the model's predictions. The overall cancer risk level is calculated by combining the results of the questionnaire-based assessment with the picture classification module using a weighted risk fusion technique. The system classifies users as low, moderate, or high risk based on the final risk score and offers suitable healthcare advice. The goal of the proposed mobile decision support system is to improve awareness, enable early screening, and help medical personnel identify patients who need more clinical investigation.
Keywords *Convolutional Neural Network(cnn);Explainable Artificial Intelligence (Xai);Decision Support System;Grad-Cam, Healthcare Informatics;Oral Cancer Risk Screening; Web Application*

1. Introduction
Oral cancer is one of the most prevalent malignancies worldwide and remains a significant contributor to cancer-related morbidity and mortality. A major challenge in managing this disease is that a large proportion of cases are detected at advanced stages, when treatment options become more complex and survival rates decline considerably. Early identification of potential risk and timely clinical evaluation play a critical role in improving patient outcomes and reducing mortality. However, many individuals do not undergo regular screening, which can delay the recognition of suspicious oral lesions and increase the likelihood of late-stage diagnosis. Conventional screening for oral cancer typically involves clinical visual examination performed by trained dental professionals or oncologists, followed by confirmatory diagnostic procedures such as biopsy when abnormal lesions are suspected. Although these methods are reliable, they require specialized medical expertise, appropriate clinical facilities, and patient awareness of the importance of routine screening. These factors can limit the frequency and accessibility of early screening, highlighting the need for supportive technologies that can assist in preliminary risk identification and encourage timely medical consultation. Recent advancements in artificial intelligence and deep learning have created new opportunities for the development of intelligent healthcare support systems. In particular, Convolutional Neural Networks (CNNs) have demonstrated strong capabilities in analyzing medical images and identifying patterns associated

with various diseases. These models are capable of automatically learning complex visual features, making them suitable for tasks such as lesion detection and medical image classification. At the same time, the widespread adoption of smartphones and web-based technologies has enabled the development of mobile-accessible healthcare tools that can support early screening and health awareness. Motivated by these technological developments, this research proposes a mobile-accessible AI-based decision support system for early oral cancer risk screening. The proposed system combines image-based analysis of intraoral photographs using deep learning models with questionnaire-based evaluation of behavioral and clinical risk factors. To improve transparency and interpretability of the AI predictions, the system also incorporates Explainable Artificial Intelligence (XAI) techniques, enabling visualization of image regions that influence the model's decisions. By integrating these components within a smartphone-accessible platform, the system aims to provide an accessible and interpretable screening support tool that assists in identifying individuals who may require further clinical evaluation.

2. The Proposed Design Aims to Achieve the Following Objectives

- To develop a mobile-accessible web-based decision support system that enables users to perform preliminary oral cancer risk screening through a simple and user-friendly interface.
- To design and implement an AI-based image analysis module using a Convolutional Neural Network (CNN) capable of screening intraoral images and identifying visual patterns associated with suspicious oral lesions..
- To integrate a structured questionnaire-based risk assessment mechanism that evaluates behavioral and clinical risk factors such as lifestyle habits, medical history, and oral health indicators.
- To incorporate Explainable Artificial Intelligence (XAI) techniques, specifically Gradient-weighted Class Activation Mapping (Grad-CAM), to improve model transparency by highlighting image regions that influence the prediction outcome.
- To implement a weighted risk fusion approach that combines the CNN-generated probability score with questionnaire-based risk factors in order to produce a more comprehensive risk evaluation.
- To generate a confidence-aware risk categorization that classifies users into different screening levels and provides appropriate healthcare recommendations.
- To design a scalable and modular system architecture that supports future integration of fully trained deep learning models, expanded datasets, and clinical validation
- To provide an interpretable screening output with visual explanation and risk assessment report, supporting early awareness and encouraging timely clinical consultation.

3. Literature Survey

Initial research efforts in automated oral cancer screening mainly focused on image-processing-based systems designed to assist in early lesion identification. Pragna et al. [1] introduced a computational framework that utilized image analysis techniques to generate early health alerts by detecting abnormal patterns in oral images. A significant advancement in explainable deep learning was later introduced by Selvaraju et al. [2] through the development of Gradient-weighted Class Activation Mapping (Grad-CAM). This method allows visual interpretation of Convolutional Neural Network predictions by highlighting the regions of an image that influence the model's decision, which is particularly valuable in medical image analysis where transparency and interpretability are essential. Further studies emphasized the increasing role of artificial intelligence in supporting early oral cancer detection. Hegde et al. [3] discussed how AI-based techniques can assist healthcare professionals in identifying potential cases at earlier stages, thereby improving diagnostic efficiency. Systematic reviews conducted by K. C. et al. [4] and González-Ruiz et al. [5] analyzed various AI-driven approaches used in oral cancer detection and highlighted the challenges associated with identifying early-stage lesions due to their subtle visual characteristics. Talwar et al. [6] demonstrated the practicality of smartphone-based screening systems that combine mobile imaging with AI analysis, indicating the potential of portable screening solutions. Similarly, Yang et al. [7] explored deep learning-based frameworks that integrate visualization techniques with automated lesion detection, improving both model performance and interpretability.In more recent work, research has increasingly focused on optimizing deep learning models and exploring mobile imaging technologies for healthcare applications. Raval and Undavia [8] investigated different CNN architectures to evaluate their effectiveness in detecting oral cancer from medical images. Alm and Elseragy [9] examined AI-assisted smartphone imaging systems and demonstrated their potential in supporting early screening through mobile platforms. Additional studies have presented various AI-based predictive and diagnostic models for oral cancer risk evaluation [10]–[12]. Swamikannan et al. [13] further highlighted the role of mobile computer vision technologies in healthcare applications, particularly for disease screening and monitoring. Kavuluri and Danwada [14] conducted a comprehensive review of AI-based oral cancer detection techniques, outlining current methodologies and their practical applications. Comparative studies examining clinical diagnostic methods and deep learning approaches were also presented in [15] and [16], providing insights into the strengths and limitations of automated detection systems. More recent investigations from 2025 onward have focused on improving model transparency, optimization strategies, and research developments in the field. Abbas et al. [17] emphasized the importance of Explainable Artificial Intelligence (XAI) in clinical decision support systems to enhance trust and interpretability of AI-generated predictions. Systematic studies exploring smartphone-based screening frameworks and optimized CNN architectures were reported in [18] and [19]. Additionally, bibliometric analyses and research related to biomarker-based detection approaches have been explored in studies such as [20]–[22]. Vijayan et al. [23] highlighted the growing effectiveness of mobile health technologies in supporting early disease detection and healthcare interventions. Further research comparing AI-based systems with clinician performance, as well as exploring personalized treatment approaches, was presented in [24] and [25]. Overall, existing literature demonstrates significant progress in the use of CNN-based medical image analysis, mobile health technologies, and explainable AI techniques for oral cancer detection. However, many existing systems primarily focus on individual components such as image classification or AI-based prediction. There remains limited research integrating multi-image intraoral analysis, questionnaire-based behavioral risk evaluation, Grad-CAM-based explainability, and confidence-aware decision support within a single smartphone-accessible platform. The system proposed in this study aims to address this gap by combining these components into a unified framework designed to support early oral cancer risk screening and provide interpretable screening assistance.

4. Prosposed System Design and Implementaion

The proposed system presents a mobile-based AI decision support platform for early oral cancer risk screening. The system integrates deep learning-based image analysis with behavioral risk assessment to assist in identifying individuals who may be at higher risk of developing oral cancer. By combining these two sources of information, the platform provides an accessible and efficient preliminary screening tool that can support early medical consultation.

The system is implemented using a web-based client–server architecture, allowing users to access the platform through smartphone browsers without requiring installation of a dedicated mobile application. This design improves accessibility while maintaining flexibility for future system expansion..The overall framework consists of three major components: data acquisition, AI-based image analysis, and integrated risk assessment. The workflow begins with the collection of intra-oral images and user health information, followed by deep learning-based screening and risk score generation.

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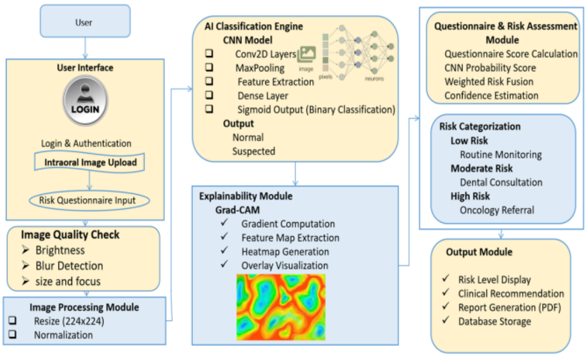

Figure 1 **Proposed sytem Design**

4.1. Dataset Collection and Preparation

To develop the image screening model, a dataset consisting of intra-oral images representing both normal oral conditions and potentially abnormal lesions was collected from publicly available medical imaging repositories and curated datasets used for oral disease research.

The dataset was organized into two primary categories:

- Class 0 – Normal oral tissue
- Class 1 – Suspicious lesion or abnormal tissue

Before training the model, several preprocessing operations were performed to improve data consistency and model performance. All images were resized to a fixed resolution suitable for CNN processing, and pixel values were normalized to maintain uniform input distribution. To improve model generalization and reduce overfitting, data augmentation techniques such as horizontal flipping, rotation, and brightness adjustments were applied. The prepared dataset was then divided into training and validation subsets, enabling the model to learn discriminative features while allowing performance evaluation during training.

4.2. CNN-Based Binary Classification Model

The core analytical component of the system is a Convolutional Neural Network (CNN) designed to perform binary classification of intra-oral images. CNNs are particularly effective in medical imaging applications because they can automatically extract hierarchical spatial features from visual data.

The CNN model was trained using labeled images from the prepared dataset. During the training phase, the network learned to identify visual patterns associated with suspicious oral lesions by adjusting its internal parameters through backpropagation and gradient-based optimization.

The final layer of the CNN produces a probability score indicating whether the input image belongs to the normal class or the abnormal lesion class. Based on this probability value, the system classifies the uploaded image into one of the two screening categories.This binary classification approach enables the system to perform rapid and automated preliminary screening, assisting in identifying cases that may require further clinical examination.

4.3. Explainable AI Using Grad-CAM

In medical applications, transparency and interpretability are critical to building trust in AI-assisted decisions. To address this requirement, the proposed system incorporates Explainable Artificial Intelligence (XAI) techniques using Gradient-weighted Class Activation Mapping (Grad-CAM). Grad-CAM generates visual heatmaps that highlight the regions of the input image that contributed most strongly to the CNN's prediction. These heatmaps help users and healthcare professionals understand the reasoning behind the model's decision. By visually indicating suspicious regions within the oral cavity, the Grad-CAM visualization improves interpretability and supports better understanding of the screening results.

4.4. Questionnaire-Based Risk Assessment

In addition to image analysis, the system collects user responses through a structured health questionnaire
The questionnaire includes questions related to:

- Tobacco consumption habits
- Alcohol intake
- Family history of cancer
- Presence of persistent oral ulcers or lesions
- Duration of oral symptoms etc

Each response is assigned a weighted score based on its clinical significance, and the cumulative score represents the user's behavioral risk level.

4.5.Risk Fusion and Decision Support

To generate a comprehensive screening result, the system Integrates image-based AI predictions with Questionnaire derived risk scores.
A weighted fusion strategy is applied to combine both components, producing an overall risk classification

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score.This integrated approach improves the reliability of Screening results by considering both visual indicators and behavioral risk factors.The final screening output includes

- Predicted risk category
- Confidence level of prediction
- Grad-CAM visual explanation
- Advisory recommendations for further medical consultation

4.6.Mobile Web Application Implementation

The entire system is implemented as a mobile-accessible web application to ensure ease of use and broad accessibility.The frontend interface is developed using HTML, CSS and JavaScript to provide a responsive design optimized for smartphone screens.The interface allows users to upload intra-oral images, complete the questionnaire, and view the screening results through a structured dashboard.

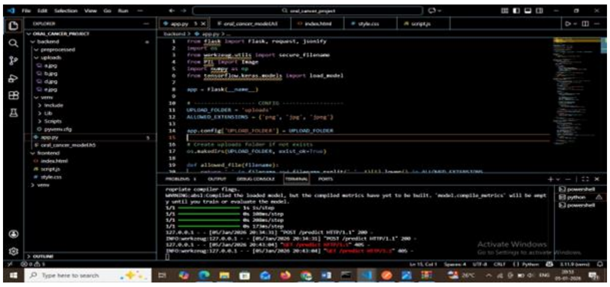

Figure 2 Programming

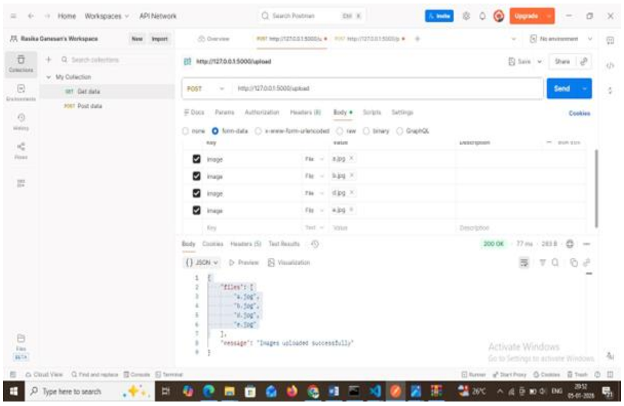

Figure 3 Features

The backend processing layer is implemented using the Flask framework, which manages image processing, AI model inference, questionnaire scoring, and generation of screening outputs. Communication between the frontend and backend is handled through RESTful APIs that transmit data securely.This implementation ensures efficient processing while maintaining flexibility for future system improvements.

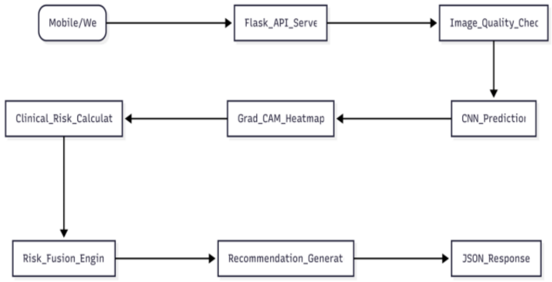

Figure 3 Flow of system

4.7. System Integration

All components of the proposed system—including image acquisition, CNN-based analysis, Grad-CAM visualization, questionnaire evaluation, and risk fusion—are integrated into a unified workflow.The system processes user inputs sequentially through these modules and generates an interpretable screening result that can assist in early detection awareness.By combining AI-driven image analysis with user-provided health information, the proposed platform demonstrates how mobile technology and artificial intelligence can be leveraged to support accessible and scalable oral cancer risk screening.

5. Methodology

The proposed system follows a hybrid screening methodology that integrates deep learning–based image analysis with behavioral risk assessment to support early identification of oral cancer risk. The objective of this methodology is to combine visual evidence from intra-oral images with clinically relevant lifestyle information in order to generate a more reliable preliminary screening outcome.The first component of the methodology focuses on image-based analysis. Intra-oral images captured using smartphone cameras are processed and analyzed using a Convolutional Neural Network (CNN) model trained to identify visual patterns associated with oral abnormalities. CNN architectures are widely used in medical image analysis due to their ability to automatically extract hierarchical spatial features such as texture variations, lesion boundaries, and irregular tissue structures. By learning these visual characteristics during training, the model can distinguish between normal oral tissue and potentially suspicious lesions. Before feeding images into the deep learning model, a set of image preprocessing techniques is applied to ensure consistency in input data. These include resizing images to a standardized resolution, normalization of pixel intensities, and augmentation strategies that improve model robustness by exposing it to variations in orientation, lighting, and contrast. These preprocessing operations help the CNN model learn generalized representations rather than memorizing specific training samples. In addition to image analysis, the proposed methodology incorporates a questionnaire-based risk evaluation mechanism. Oral cancer is strongly associated with behavioral and lifestyle factors such as tobacco usage, alcohol consumption, and persistent oral symptoms. Therefore, the system collects structured information from users through a questionnaire designed to capture these risk indicators. Each response contributes to an overall behavioral risk score based on predefined clinical weights. The outputs from the CNN image classification model and the questionnaire-based risk assessment are then integrated using a risk fusion strategy. This combined analysis ensures that the final screening decision considers both visual evidence from oral images and patient-related risk factors. By combining these complementary sources of information, the system improves the reliability of the screening process compared to relying on image analysis alone. To enhance interpretability of the AI predictions, the system also integrates Explainable Artificial Intelligence (XAI) techniques. Specifically, Gradient-weighted Class Activation Mapping (Grad-CAM) is applied to visualize the regions within an oral image that contribute most strongly to the model's prediction. This visualization helps users and healthcare professionals understand the reasoning behind the AI-generated screening result.Through this methodology, the proposed system provides a mobile-accessible decision support platform capable of performing automated preliminary screening while maintaining transparency and interpretability in its predictions.

6. Algorithms Used in System

The primary algorithm used in the proposed system is a Convolutional Neural Network (CNN) for binary image classification, supported by Grad-CAM for explainability and a weighted risk fusion mechanism for integrating behavioral risk factors.

6.1. Convolutional Neural Network (CNN)

A Convolutional Neural Network is a deep learning architecture specifically designed to process visual data. It consists of multiple interconnected layers that automatically learn to extract meaningful features from images. The CNN model used in this system is trained to perform binary classification, where the input intra-oral image is categorized as either normal oral tissue or suspicious lesion. The convolutional layers within the network apply learnable filters to the input images in order to detect low-level features such as edges, textures, and color patterns. As the data progresses through deeper layers of the network, the model captures more complex and abstract visual characteristics associated with abnormal oral tissue. Pooling layers are incorporated to reduce the spatial dimensions of feature maps, which improves computational efficiency and enhances the model's ability to generalize. The extracted features are then passed through fully connected layers that perform the final classification task. The output layer produces a probability score indicating the likelihood that the image belongs to the abnormal lesion category.

6.2. Grad- CAM Explainability Algorithm

To provide interpretability for the CNN predictions, the system utilizes Gradient-weighted Class Activation Mapping (Grad-CAM). Grad-CAM is an explainable AI technique that identifies the regions within an image that have the greatest influence on the model's decision. The algorithm works by computing gradients of the target class with respect to the feature maps generated by the final convolutional layers. These gradients are used to determine the importance of each feature map in the prediction process. A weighted combination of these maps produces a heatmap visualization, highlighting areas of the image that contributed most strongly to

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the classification. In the context of oral cancer screening, this heatmap allows users to visually observe which regions of the oral cavity were considered suspicious by the AI model, thereby improving trust and transparency.

6.3. Risk Fusion Mechanism

To produce a comprehensive screening outcome, the system integrates the CNN-based image prediction with the questionnaire-derived behavioral risk score. This integration is achieved through a weighted fusion approach in which both components contribute to the final risk estimation.The risk fusion mechanism ensures that the final screening result reflects both visual abnormalities detected in oral images and known lifestyle risk factors associated with oral cancer. This combined approach enhances the overall reliability of the system and provides a more balanced decision support output.

7. System Modules

The proposed oral cancer screening system is structured into several interconnected modules that process user input, perform AI-based analysis, and generate interpretable screening results. Each module is responsible for a specific stage of the workflow, enabling efficient data processing and reliable risk assessment.

7.1.User Interface and Authentication Module

The User Interface module acts as the primary interaction point between the user and the screening system. It provides a mobile-friendly web interface that allows individuals to access the application through a smartphone or browser-based platform. This module manages user authentication through a login mechanism to ensure secure access to the system. Once authenticated, users can upload intraoral images and provide responses to the health risk questionnaire. The interface is designed to guide users through the screening process in a structured manner, ensuring that all required information is captured before proceeding to the analysis stage.

7.2. Image Quality Check Module

The Image Quality Check module evaluates whether the uploaded intraoral images are suitable for automated analysis. Images captured using mobile devices may vary in clarity and lighting conditions, which can affect model predictions. This module analyzes several quality parameters including image brightness, blur level, and focus. It also verifies that the image size and orientation meet the required specifications for the deep learning model. Images that fail to meet quality standards can be rejected or flagged for re-upload to ensure reliable screening results. By filtering out poor-quality images at an early stage, this module improves the overall robustness and accuracy of the AI-based classification process.

7.3. Image Processing Module

The Imagez Processing module prepares the validated images for input into the deep learning model. Since neural networks require consistent input dimensions and normalized pixel values, preprocessing operations are performed before classification. The images are resized to a standard resolution of 224 × 224 pixels, which matches the input size required by the CNN model. Pixel normalization is then applied to scale image intensities within a uniform range. These preprocessing operations help stabilize the learning process and ensure that the CNN receives structured input data for feature extraction.

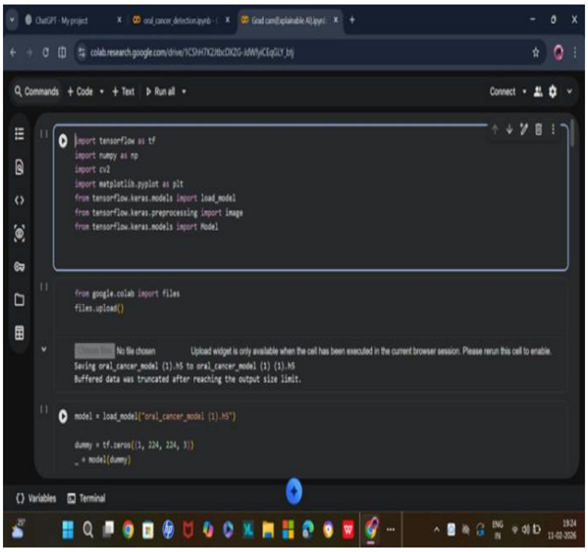

Figure 4 Data Processing

7.4. AI Classification Engine (CNN Model)

The AI Classification Engine is the core analytical component of the system. It utilizes a Convolutional Neural Network (CNN) to analyze intraoral images

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and identify patterns associated with abnormal oral tissue. The CNN architecture consists of multiple Conv2D layers that extract spatial features from the images. These convolution layers are followed by max-pooling layers that reduce spatial dimensions while preserving important features. The extracted feature maps are then passed to dense layers, where high-level representations are learned. The final output layer uses a sigmoid activation function to perform binary classification. Based on the predicted probability, the system categorizes the image into two possible classes:

- 1.Normal oral tissue
- 2.Suspected abnormal lesion

This classification result forms the primary AI-driven indicator of oral cancer risk.

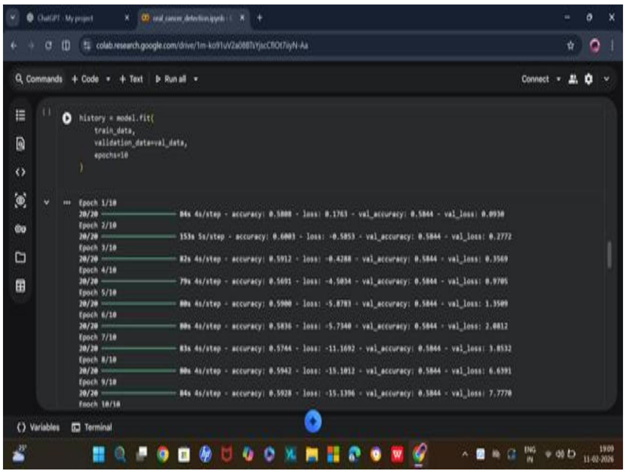

Figure 5 Data Processing

7.5.Explainability Module (Grad-CAM)

To improve transparency in the AI predictions, the system integrates an Explainability Module based on Gradient weighted Class Activation Mapping (Grad-CAM). Grad-CAM analyzes the gradients flowing through the CNN model to determine which feature maps contributed most significantly to the prediction. These gradients are used to generate a heatmap visualization that highlights the regions of the image that influenced the classification result. The generated heatmap is overlaid on the original intraoral image, allowing users and healthcare professionals to visually identify the areas that the AI model considered suspicious. This interpretability mechanism helps build trust in the system and provides additional insight into the AI decision-making process.

7.6.Questionnaire and Risk Assessment Module

The Questionnaire and Risk Assessment module collects behavioral and medical information from the user through a structured questionnaire. The questionnaire evaluates factors that are clinically associated with oral cancer risk. User responses are processed to calculate a questionnaire risk score based on predefined weights assigned to each risk factor. At the same time, the probability output produced by the CNN model is considered as the image-based risk score. A weighted risk fusion mechanism is applied to combine both the CNN prediction probability and the questionnaire score. This integration produces a comprehensive risk estimate that reflects both visual indicators and lifestyle-related risk factors.In addition, the module a confidence estimation value that represents the reliability of the generated risk assessment.

7.7.Risk Categorization Module

After computing the overall risk score, the system classifies the screening result into predefined risk levels. This categorization helps simplify interpretation and guide appropriate follow-up actions.The risk levels are divided into three categories

Low Risk: Indicates minimal risk based on image analysis and questionnaire results. Routine monitoring is recommended.

Moderate Risk: Suggests potential indicators that may require professional dental consultation.

High Risk: Indicates a higher probability of abnormal findings and recommends referral to an oncology specialist for further clinical examination.

This structured categorization ensures that the screening output is easy to interpret and clinically meaningful[26].

7.8. Output and Reporting Module

The Output Module is responsible for presenting the final screening results to the user through the system dashboard. The module displays the predicted risk level along with

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relevant visual explanations and recommendations. The results include the risk category, Grad-CAM visualization, and clinical guidance for further action. In addition, the system generates a PDF report summarizing the screening outcome, which can be downloaded or shared with healthcare professionals. The module also stores screening records in a database for future reference and monitoring. This capability allows the system to maintain a history of user screenings and supports long-term health tracking.

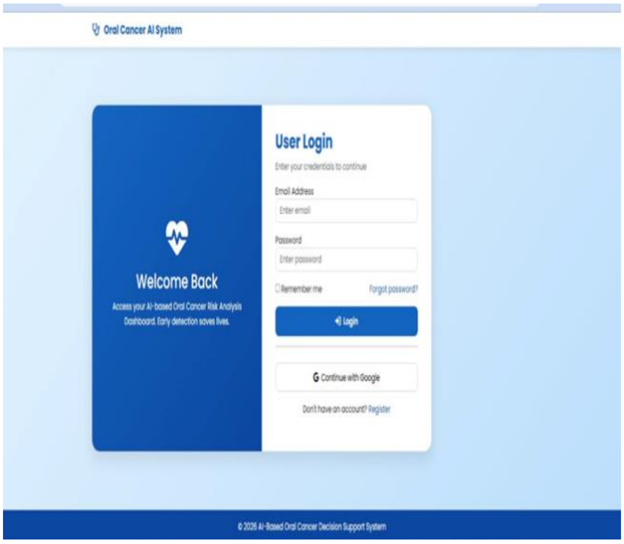

Figure 6 Login

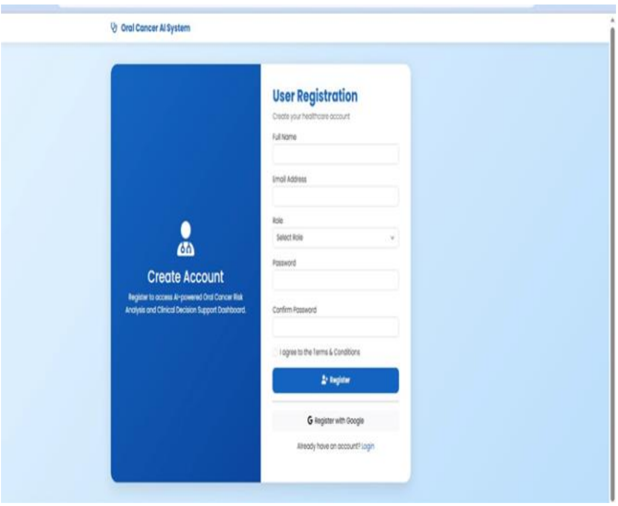

Figure 7 Registration

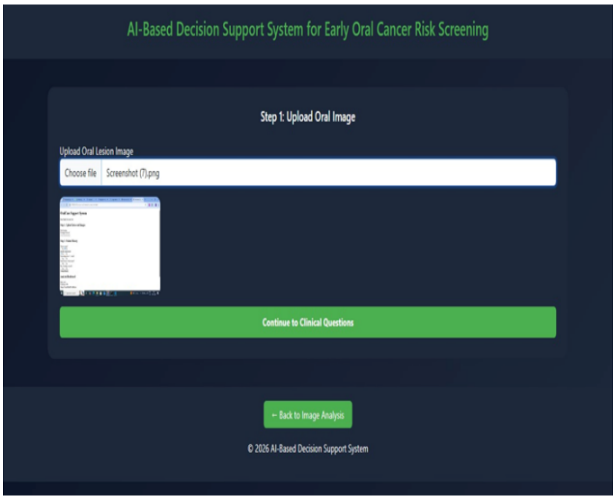

Figure 8 Screening

Figure 9 Continue

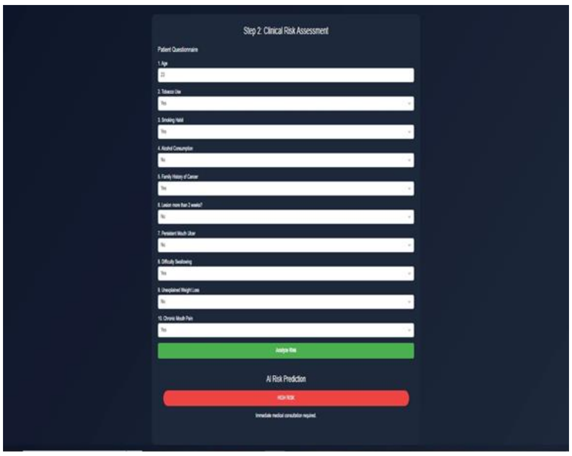

Figure 10 Result

8. Future Work

Future improvements will focus on enhancing both the technical performance of the system and its practical applicability in clinical environments. The following developments are planned to further strengthen the proposed framework

8.1.Dataset Expansion and Model Improvement

The oral cancer image dataset will be expanded by incorporating a larger number of high-quality and clinically verified intra-oral images. A more diverse dataset will allow the CNN model to learn additional visual patterns, improving its sensitivity and specificity in detecting suspicious lesions

8.2.Clinical Validation

The predictions generated by the CNN model, along with the Grad-CAM visual explanations, will be evaluated and validated by dental and oncology specialists. This step will ensure that the system's outputs align with real clinical observations and support reliable screening outcomes.

8.3.Confidence Calibration

Future work will incorporate calibration techniques to improve the reliability of prediction probabilities. Better confidence estimation will enhance trust in the system's screening results and provide more meaningful decision support.

8.4.Improved User Accessibility

The system interface will be enhanced with multilingual support and improved usability features. This will make the platform accessible to users from diverse linguistic and demographic background.

8.5.Real-World Deployment and Integration

The system will be deployed in healthcare screening environments to evaluate its practical usability. Integration with clinical workflows and healthcare platforms will be explored to support real-world adoption.

Conclusion

This study presented a web-based artificial intelligence decision support system designed to assist in early oral cancer risk screening. The proposed framework integrates CNN-based binary image classification, questionnaire-based behavioral risk assessment, and Grad-CAM explainable AI techniques to create an interpretable and accessible screening platform. The deep learning model was trained using publicly available oral cancer image datasets on GPU-accelerated environments, enabling efficient feature extraction and classification of intra-oral images into normal and suspected abnormal categories. The trained model was deployed within a Flask-based backend architecture, allowing real-time inference through RESTful APIs. Through a mobile-accessible web interface, users can upload intra-oral images, provide relevant health information, and receive automated screening outputs that include risk predictions, confidence estimates, and visual explanations. This end-to-end implementation demonstrates the practical feasibility of combining artificial intelligence, explainable models, and mobile web technologies to support early risk awareness. Although further dataset expansion, large-scale model refinement, and clinical validation remain ongoing areas of research, the current system successfully demonstrates the functional workflow, modular architecture, and scalability of the proposed approach. The system is designed strictly as a screening and decision-support tool, ensuring responsible and ethical use in healthcare settings. Overall, the proposed framework establishes a strong foundation for developing scalable, interpretable, and accessible AI-assisted screening solutions, with promising potential for future integration into real-world healthcare environments.

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