PANIMALAR ENGINEERING COLLEGE

OralGuard AI:Intelligent Vision-Based Oral Cancer Screening for Low-Resource Environment

Team Members :M.U.Easwari(211423104150), M.H.Evelyn Antonica(211423104155)

Batch Number:B 10

Department:Computer Science and Engineering

Guide Name:Dr.S.T.SANTHANALAKSHMI,M.Tech.,Ph.D.,

Co-ordinator Name:Dr.T.JACKULIN, M.E., Ph.D.,

SDG Goal:Good Health and Well-Being

Abstract

- Oral cancer is a major health concern in India
- Over 77,000 new cases reported annually
- Majority diagnosed at late stages due to lack of screening
- AI and Computer Vision used for early detection
- Low-cost, lightweight ML model designed
- Works offline and runs on minimal hardware
- Supports SDG 3 – Good Health and Well-being
- Helps rural health centers perform first-level screening

Introduction

- Oral cancer is a common and fatal disease in developing nations
- High mortality due to delayed diagnosis
- Conventional methods (biopsy, clinical check) are:

  Expensive

  Time-consuming

  Not available in rural areas
- AI and Computer Vision offer affordable alternatives
- Smart AI system enables early oral lesion detection
- Reduces dependency on advanced medical infrastructure

Objective

- Design an AI-based diagnostic model for oral cancer
- Utilize image processing and ML to classify oral images
- Ensure accessibility in rural and low-resource areas
- Develop lightweight, terminal-based prediction tool
- Minimize hardware and internet dependency
- Provide quick and reliable results
- Reduce oral cancer mortality rate through early detection

Literature Survey

S.No	Title/Publications	Techniques adopted	Results	Conclusions/Limitations
01.	**"Deep Learning for Early Detection of Oral Cancer using CNN-Based Image Classification"** IEEE Access, Vol. 10, 2022	Convolutional Neural Network (CNN) Preprocessing using Histogram Equalization Transfer Learning (ResNet-50 / VGG-16) Data Augmentation (rotation, flipping, zooming)	Achieved **accuracy of 92.7%** using fine-tuned ResNet-50 Sensitivity and specificity showed improved detection in early-stage lesions ROC-AUC score: **0.94**, indicating strong classification performance Outperformed traditional SVM and handcrafted feature methods	Deep CNN models are effective in identifying oral cancer through medical images Requires **high-quality annotated datasets** for better generalization **Black-box nature** of deep learning makes interpretability a challenge Performance may drop with **low-light or poor-quality images**

S.No	Title/Publications	Techniques adopted	Results	Conclusions/Limitations
02.	**"Active Reranking for Web Image Search"** IEEE Transactions on Image Processing, Vol. 19, No. 3, March 2010	**Active Re-ranking** (User-in-the-loop refinement) **Structural information-based active sample selection** **Local-global discriminative dimension reduction algorithm** Feature-based image clustering and selection	Significantly **reduced ambiguity** in image search results Improved accuracy by capturing **user search intention** Enabled **simultaneous access** and relevance feedback for better image selection Achieved better precision than traditional relevance feedback models	Effective for personalizing image results using user feedback Requires **manual labeling** for optimal reranking Depends on **structural similarity**, may fail with noisy or mislabeled images **Not suitable** for online image datasets with **unstructured filenames/tags** May suffer from **scalability issues** in real-time search engines

S.No	Title/Publications	Techniques adopted	Results	Conclusions/Limitations
05.	**IntentSearch: Capturing User Intention for One-Click Internet Image Search** IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 34, NO. 7, JULY 2012	Novel approach for oral cancer image search **Adaptive similarity** learning **Keyword expansion**, **image pool expansion**, and **visual query expansion** Uses a **single query image** to capture diagnostic intent	Effectively captures **doctor's diagnostic intent** from one image Reduces ambiguity in early lesion retrieval Avoids need for multiple user interactions Improved performance in identifying visually similar oral lesions	**Does not store user search history**, limiting personalization **Processing time increases** for large oral cancer datasets Risk of **duplicate lesion images** being retrieved Needs optimization for real-time clinical usage

S.No	Title/Publications	Techniques adopted	Results	Conclusions/Limitations
08.	**Machine Vision Based Defect Detection System for Oral Liquid Vial** Proceedings of the 13th World Congress on Intelligent Control and Automation, IEEE, July 2018	Machine vision-based defect detection system for **oral liquid vial** inspection **Horizontal intercept projection** for vial cap defect detection **Black top-hat transform** and **multi-feature analysis** for detecting vial body cracks Features used: area, perimeter, max distance, contour branches, roundness, and curvature High-speed **industrial imaging system** and real-time image processing modules	Detection accuracy: **Vial cap**: 98.2% **Vial body**: 99.8% Execution time: Vial cap: 35 ms Vial body: 58 ms System outperformed manual inspection in both accuracy and speed Successfully identified cap scratches and vial body cracks in real-time industrial setting	Highly effective for real-time defect detection in oral liquid vials Eliminates human error and speeds up inspection process Focused only on **vial surface defects**, not on liquid content or internal impurities Limited to **fixed imaging configurations** – less adaptable to vial variations or layout changes Not tailored for **medical oral cancer image detection** but useful in industrial oral product quality assurance

S.No	Title/Publications	Techniques adopted	Results	Conclusions/Limitations
07.	**Automated Detection and Classification of Oral Lesions Using Deep Learning for Early Detection of Oral Cancer** Published in International Journal of Research Publication and Reviews, Vol. 3, Issue 7, July 2022	Deep Learning-based classification using **Convolutional Neural Networks (CNNs)** Preprocessing of oral images using **data augmentation** and **grayscale conversion** Implementation of **custom CNN architecture** for classification Dataset manually collected and pre-labeled into categories (Normal, Leukoplakia, Oral Cancer) Training and testing using Keras and TensorFlow frameworks	Achieved **accuracy of 92.3%** for classifying oral lesion images The CNN model effectively distinguished between normal, precancerous, and cancerous lesions Confusion matrix and accuracy graphs showed good performance metrics Proved that deep learning could be a reliable early diagnostic tool for oral cancer detection	Model performs well with a **limited dataset**; larger datasets needed for better generalization Real-time integration into **clinical systems not implemented** Further optimization required for **lighting variations and low-resolution images** Manual annotation is time-consuming and may introduce **human bias** Model interpretability remains a challenge in medical environments

Problem Statement

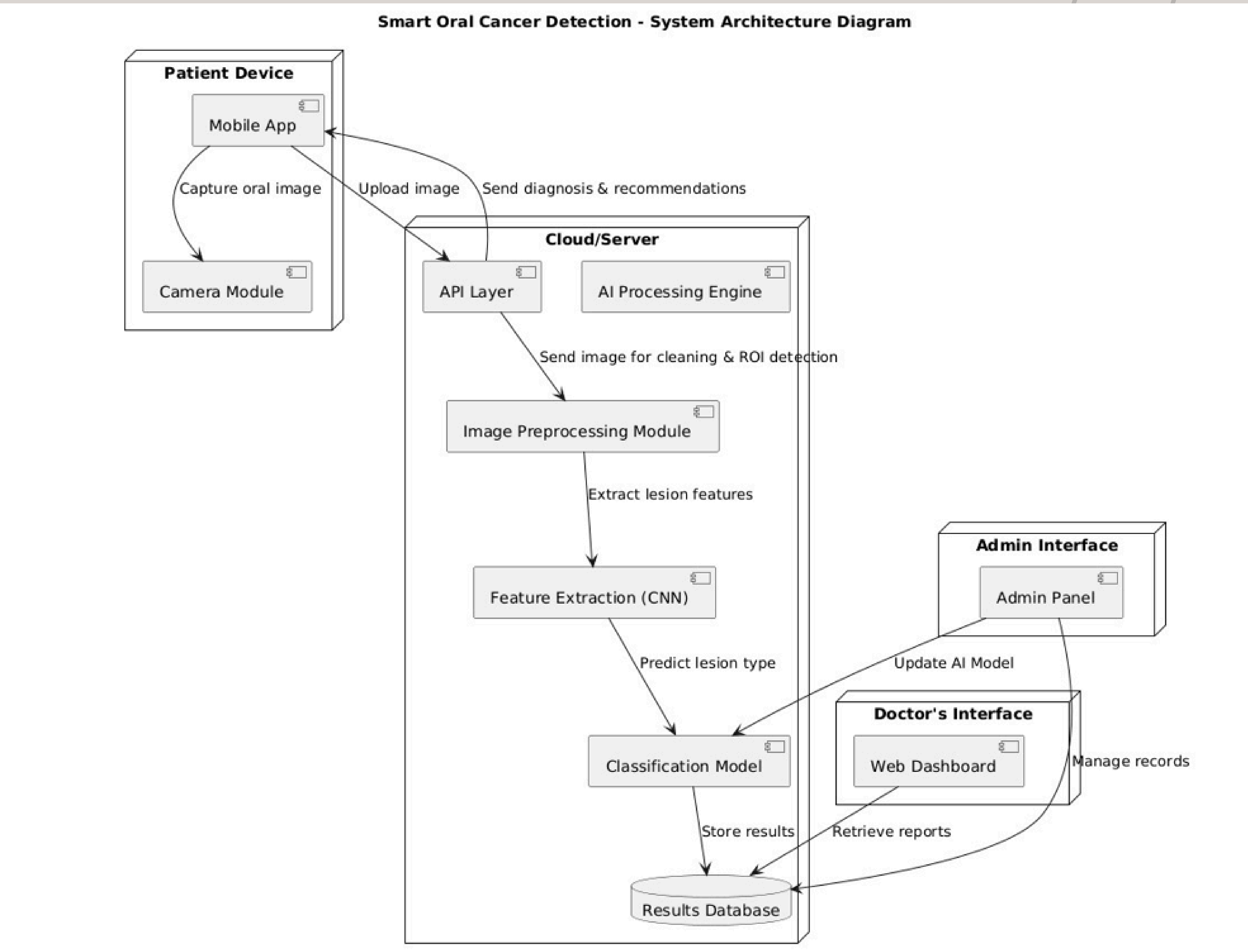
- Late diagnosis leads to high mortality
- Lack of accessible and affordable screening tools
- Existing AI systems require high-end infrastructure
- Rural regions lack oncologists and screening kits
- Need for:

  Lightweight, terminal-based model

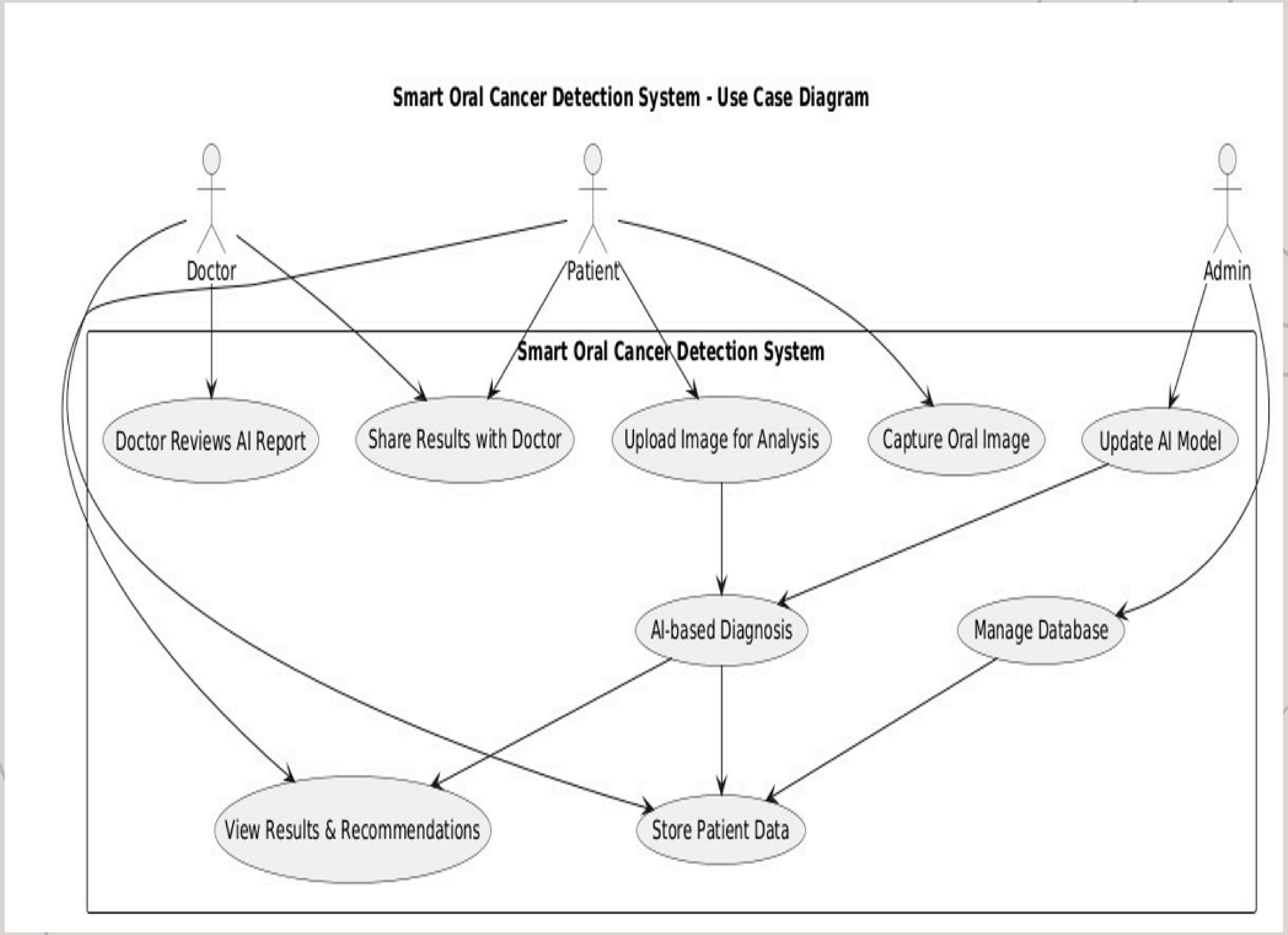
  Cost-effective solution

  Offline operation capability

Architecture Diagram



Use Case Diagram



System Modules

- Image Acquisition: Captures image via smartphone
- Preprocessing: Noise removal, normalization, resizing
- Feature Extraction: Using HOG, GLCM
- Model Training: SVM, Logistic Regression, CNN
- Prediction: Classification as “Healthy” or “Cancerous”
- Evaluation: Measures accuracy, recall, F1-score

Algorithms / Methodology

- **Image Preprocessing:**
  - Gaussian & Median Filters
  - Normalization and Augmentation
- **Feature Extraction:**
  - Edge, Color, Texture Detection
  - HOG and GLCM
- **Model Training:**
  - Logistic Regression
  - SVM
  - Shallow CNN
- **Validation:**
  - 80% Training / 20% Testing
  - K-Fold Cross Validation

Testing

- **Dataset**:

  Kaggle Oral Cancer Image Dataset

- **Tools Used:**

  Python

  TensorFlow

  OpenCV

  Scikit-learn

- **Evaluation Parameters:**

  Accuracy

  Precision

  Recall

  F1-Score

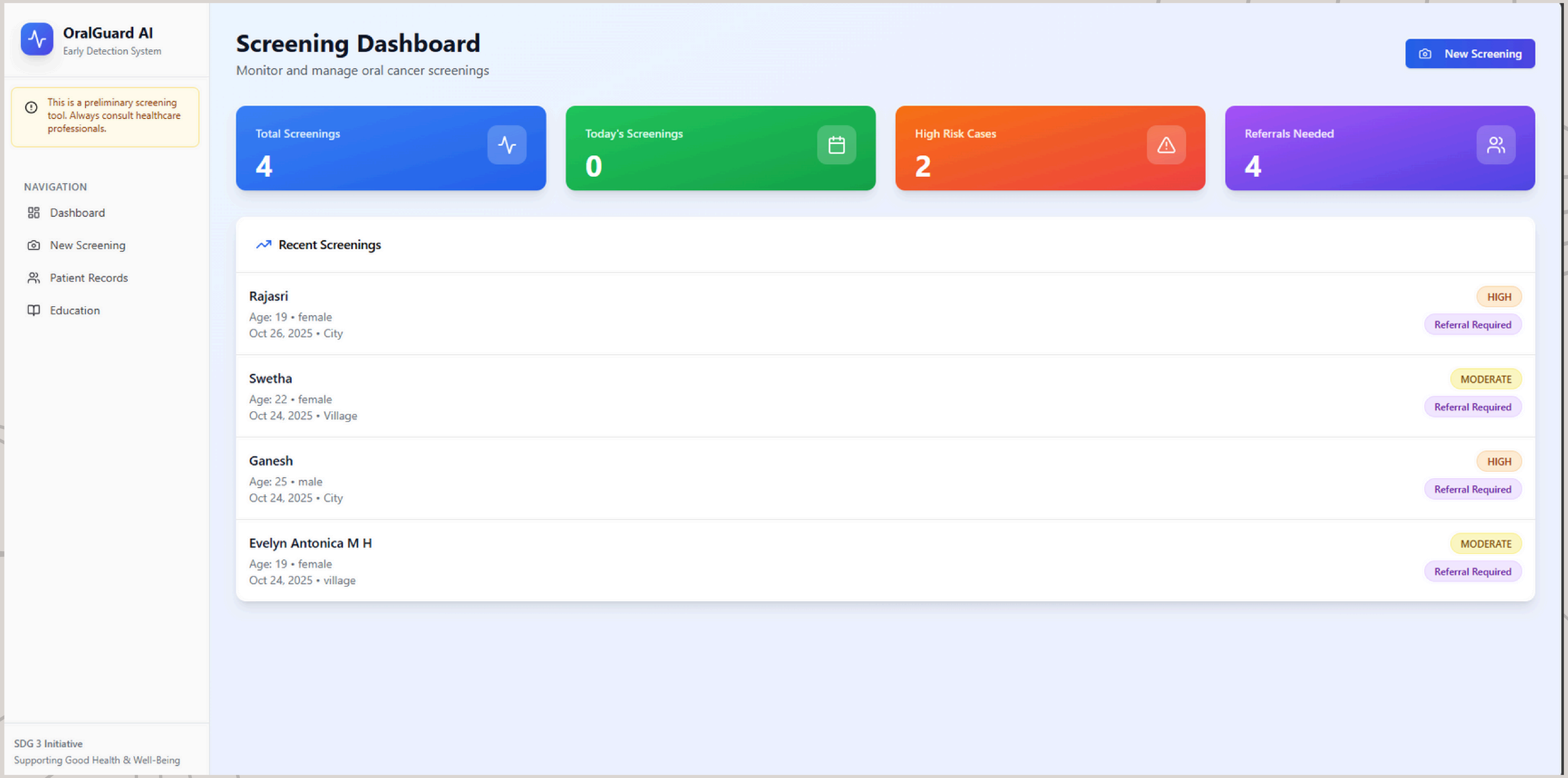
Test Cases / Validation

Test Case ID	Input	Expected Output	Result
TC01	Oral Image (Healthy)	Healthy	Passed
TC02	Oral Image (Cancerous)	Cancerous	Passed
TC03	Low Quality Image	Rejected / Reprocessed	Passed
TC04	Different Lighting Image	Accurate Classification	Passed

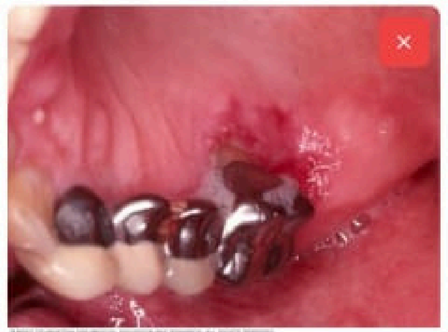
Performance Analysis

- Logistic Regression: Moderate Accuracy (85%)
- SVM: Better Precision (88%)
- Shallow CNN: 88–90% Accuracy
- ResNet50: 94% but needs GPU
- Shallow CNN = Best trade-off between speed and accuracy
- Lightweight models suitable for rural deployment

Screenshots



Oral Cavity Image



Analyze Image

AI Analysis Results

RISK LEVEL MODERATE

OBSERVATIONS

The image shows an area inside the oral cavity that includes visible teeth and adjacent mucosal tissue. There appears to be some redness along with a potential ulceration or sore near a metal dental restoration (crown). The presence of the metallic dental work suggests previous dental procedures. No obvious white patches (leukoplakia) or red patches (erythroplakia) were observed. However, the irritation or soreness might be indicative of underlying issues.

SPECIFIC CONCERNS

- Redness possibly indicating inflammation or irritation
- Loosening teeth might correlate with underlying gum disease or oral pathology

RECOMMENDATIONS

It is recommended that the patient consult with a qualified healthcare professional, such as a dentist or oral surgeon, for a thorough examination and potential biopsies to identify any serious conditions, as well as to address the loose teeth issue and assess oral health further.

Professional referral recommended. Please ensure patient sees a qualified healthcare provider.

Save Screening Record

OralGuard AI
Early Detection System

This is a preliminary screening tool. Always consult healthcare professionals.

NAVIGATION

- Dashboard
- New Screening
- Patient Records
- Education

SDG 3 Initiative
Supporting Good Health & Well-Being

Patient Information

Patient Name *
Ganesh

Age *
25

Gender
Male

Phone
9845670231

Location
City

Symptoms & Risk Factors

Reported Symptoms

- [ ] White or red patches in mouth
- [ ] Persistent mouth sores
- [ ] Difficulty swallowing
- [ ] Lump or thickening in cheek
- [x] Numbness in tongue or mouth
- [x] Pain in mouth or ear
- [ ] Loose teeth
- [ ] Difficulty moving jaw or tongue

Risk Factors

- [ ] Tobacco use (smoking/chewing)
- [x] Alcohol consumption
- [ ] Betel nut/Pan use
- [ ] Poor oral hygiene
- [ ] HPV infection
- [ ] Family history
- [ ] Previous oral cancer

Oral Cavity Image

Analyze Image

Conclusion

- Lightweight ML models feasible for oral cancer detection
- System ensures affordability and accessibility
- High accuracy achieved using shallow CNN
- Offline operation aids rural health centers
- Contributes to SDG 3 – Good Health and Well-being
- Bridges healthcare gap between urban and rural populations

Future Work

- Integration with ResNet and MobileNet
- Real-time lesion heatmap visualization
- Voice-based multilingual interface
- Mobile app integration (mHealth)
- Edge deployment on Raspberry Pi
- Continuous dataset expansion for robustness

References

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[2] Chen et al., 2024 – Attention-based deep learning for biomedical imaging

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[4] Raj et al., 2022 – CNN-based early diagnosis

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[6] Yadav & Patel, 2023 – Transfer learning methods

[7] Banerjee & Sinha, 2022 – Medical image preprocessing

[8] Jain & Sharma, 2023 – Edge AI healthcare systems

[9] Gupta & Chatterjee, 2024 – Hybrid CNN-SVM models

[10] Albahli, 2023 – Explainable AI for lesion analysis

Thank You