SMART ORAL CANCER DETECTION USING AI AND COMPUTER VISION

A SOCIALLY RELEVANT MINI PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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ABSTRACT

Oral cancer remains one of the most prevalent and deadly diseases in India, especially in rural and low-resource regions where early detection is limited due to lack of awareness and affordable screening tools. This project, “Smart Oral Cancer Detection Using AI and Computer Vision,” aims to develop a terminal-based intelligent system capable of detecting early signs of oral cancer from mouth images. The proposed system leverages image preprocessing, feature extraction, and machine learning to classify images as healthy or cancerous, enabling rapid and low-cost diagnosis without the need for specialized equipment.The project aligns with SDG 3: Good Health and Well-Being, particularly Target 3.4, which focuses on reducing premature mortality from non-communicable diseases through early detection and treatment. By using technologies such as Python, OpenCV, TensorFlow, and Keras, the solution ensures accessibility even in offline or resource-constrained environments. The system’s lightweight architecture makes it suitable for deployment in rural clinics and community health centers, empowering healthcare workers to perform initial screenings effectively.The envisioned outcome is a significant reduction in delayed oral cancer diagnoses, leading to improved survival rates and healthcare accessibility. Future enhancements include integration of deep learning models (CNN, ResNet), heatmaps, audio alerts, and multilingual support, aiming to expand usability and diagnostic accuracy.

TABLE OF CONTENTS

TITLE	PAGE NO.

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

The project **"Smart Oral Cancer Detection Using AI and Computer Vision"** aims to develop an intelligent system that can automatically detect oral cancer from digital images using Artificial Intelligence (AI) and image processing techniques. Oral cancer is one of the major health problems worldwide, especially in developing countries like India, where early detection is often limited due to lack of awareness, infrastructure, and medical specialists. The main goal of this project is to create a low-cost, efficient, and accessible diagnostic tool that can help identify oral cancer at an early stage, thereby reducing mortality rates and improving patient outcomes.

The system uses **computer vision** and **deep learning algorithms** to analyze oral cavity images and classify them as *healthy* or *cancerous*. By employing **Convolutional Neural Networks (CNNs)**, the system learns to recognize distinct patterns, textures, and color variations in images that indicate the presence of cancerous cells. The project also integrates **OpenCV** for image preprocessing and enhancement, and **TensorFlow** as the deep learning framework to train and test the model.

1.2 PROBLEM STATEMENT

Oral cancer is one of the most common and life-threatening diseases, especially in developing countries like India, where delayed diagnosis and lack of medical resources often lead to high mortality rates. Traditional diagnostic methods depend heavily on manual examination and biopsy analysis performed by trained specialists. These methods are time-consuming, costly, and not easily accessible in rural or underdeveloped regions. As a result, most patients are diagnosed only at an advanced stage of the disease, drastically reducing their chances of survival.

There is a pressing need for a low-cost, reliable, and automated system that can assist in the early detection of oral cancer using advanced technologies. With the rapid growth of Artificial Intelligence (AI) and Computer Vision, it has become possible to analyze medical images and identify patterns that may not be visible to the human eye. However, existing AI-based medical systems often require high-end hardware, internet connectivity, or complex interfaces, making them unsuitable for real-world use in low-resource healthcare environments.

Hence, the problem addressed by this project is the lack of an accessible, efficient, and intelligent system for early oral cancer detection. The goal is to design and implement an AI-based image analysis model capable of classifying oral cavity images as healthy or cancerous using deep learning and computer vision techniques.

1.3 LITERATURE REVIEW

The detection and diagnosis of oral cancer have been a major concern in the field of healthcare, as early identification plays a vital role in improving the survival rate of patients. Traditionally, oral cancer diagnosis has relied on clinical examination and biopsy procedures performed by medical professionals. However, these methods are often time-consuming, expensive, and highly dependent on the expertise of specialists. According to the World Health Organization (WHO), delayed diagnosis is one of the primary reasons for the high mortality rate of oral cancer, especially in developing countries where access to trained healthcare professionals is limited.

To overcome these limitations, researchers have explored the use of image processing and computer vision techniques for automated oral cancer detection. Early studies focused on applying basic image processing methods such as segmentation, edge detection, and thresholding to identify irregular patterns in oral cavity images. Although these traditional approaches provided some assistance in detecting abnormal regions, they lacked robustness when dealing with variations in lighting, image resolution, and patient diversity. Studies conducted by Raj et al. (2020) and Simões et al. (2021) showed that classical machine learning algorithms like Support Vector Machines (SVM) and Random Forests could be used for oral lesion classification, but their accuracy was limited and heavily dependent on manual feature extraction.

However, existing studies still face certain limitations. The availability of large, labeled oral cancer image datasets remains a challenge, leading to restricted model generalization. Moreover, few systems provide real-time, offline analysis or integrate ethical AI considerations such as data privacy, transparency, and explainability. Many models focus purely on accuracy without addressing practical aspects like usability, portability, and affordability in resource-constrained settings.

From the reviewed literature, it is evident that Artificial Intelligence and Deep Learning are transforming medical diagnostics by enabling automated, accurate, and scalable detection systems. Yet, there is a pressing need for solutions that combine **accuracy, efficiency, and accessibility**. The proposed system in this project addresses these gaps by using **MobileNetV2** for efficient feature extraction and **TensorFlow Lite** for optimized deployment. This approach offers a lightweight, low-cost, and portable AI-based tool capable of performing oral cancer screening even in areas with limited technological infrastructure. Hence, the project contributes to bridging the gap between advanced AI research and its practical application in **early oral cancer detection and preventive healthcare**.

CHAPTER 2

SYSTEM ANALYSIS

2.1 EXISTING SYSTEM

In the current healthcare scenario, the detection and diagnosis of oral cancer are primarily carried out through manual clinical examination and laboratory-based investigations. The standard procedure involves visual inspection by dentists or oncologists to identify abnormal lesions, tissue discoloration, or ulcerations in the oral cavity. If a suspicious region is found, a biopsy and histopathological test are performed for confirmation. While these traditional diagnostic methods are accurate, they are time-consuming, expensive, and heavily dependent on expert interpretation.

In rural and remote areas, there is often a shortage of trained oncologists and diagnostic facilities, leading to delayed detection and treatment. Many patients fail to receive timely medical attention due to limited accessibility, financial constraints, and lack of awareness. As a result, oral cancer is frequently diagnosed at an advanced stage, when treatment is less effective and survival chances are significantly lower.

Some advanced hospitals and research institutions have begun experimenting with AI-based diagnostic tools, but these systems usually require high computational power, continuous internet connectivity, and large annotated datasets. They are often deployed in controlled laboratory conditions rather than in real-world healthcare environments. Moreover, existing systems tend to be cloud-dependent, meaning that image data must be uploaded to remote servers for processing — a serious limitation in regions with poor network infrastructure or privacy concerns.

Another drawback of the existing systems is their lack of affordability and usability. Most AI-based medical imaging tools require costly devices and trained operators to function effectively. They are not designed for non-expert users such as primary healthcare workers or technicians in rural clinics. The absence of a simple, low-cost, and portable system limits the reach of AI in early cancer detection programs.

2.2 PROPOSED SYSTEM

The proposed system, **“Smart Oral Cancer Detection Using AI and Computer Vision,”** is designed to overcome the limitations of the existing manual and semi-automated diagnostic approaches. This system utilizes **Artificial Intelligence (AI)** and **Deep Learning** techniques to detect and classify oral cancer from medical or oral cavity images accurately and efficiently. By integrating **Computer Vision** and **Convolutional Neural Networks (CNNs)**, the proposed system can automatically analyze oral images, identify abnormal regions, and classify them as *healthy* or *cancerous* with minimal human intervention.

The main objective of this system is to provide a **fast, cost-effective, and reliable** diagnostic tool that can operate even in **rural or low-resource environments** where advanced medical infrastructure is unavailable. Unlike existing systems that depend on laboratory analysis or high-end servers, this proposed model is lightweight, portable, and capable of functioning **offline** through a simple terminal interface. This makes it accessible to healthcare workers, dentists, and technicians who may not have specialized training in oncology or AI.

Advantages of the Proposed System

- **Automation:** Reduces human dependency and subjectivity in diagnosis.
- **Accuracy:** Achieves reliable classification results using AI-driven pattern recognition.
- **Affordability:** Eliminates the need for expensive diagnostic equipment or laboratory tests.
- **Offline Functionality:** Operates without internet access, suitable for rural healthcare setups.
- **User-Friendly:** Simplified command-line interface that is easy to use for non-technical users.
- **Scalability:** Can be extended to detect other oral and facial diseases in the future.

System Outcome

The proposed system ensures early-stage detection of oral cancer, enabling timely medical intervention and improving patient survival rates. By bridging the gap between advanced AI research and practical healthcare needs, the system contributes to **Sustainable Development Goal (SDG) 3 – Good Health and Well-Being**, promoting equitable access to healthcare technology.

2.3 DEVELOPMENT ENVIRONMENT

The project **“Smart Oral Cancer Detection Using AI and Computer Vision”** was developed in a simple yet efficient computing environment that supports artificial intelligence and computer vision operations. The system was implemented using the **Python programming language (version 3.8 and above)**, as it provides strong support for deep learning, image processing, and data analysis.

The development was carried out on a **Windows 10 operating system**, though it is also compatible with **Linux (Ubuntu)** platforms. The main programming environment used was **Visual Studio Code**, along with **Jupyter Notebook** for testing and model training. To ensure modular and efficient development, version control was maintained using **Git and GitHub**.

The system utilizes several Python libraries, including **TensorFlow** and **Keras** for building and training the Convolutional Neural Network (CNN) model, **OpenCV** for image preprocessing and feature extraction, **NumPy** and **Pandas** for data handling and matrix operations, and **Matplotlib** for visualizing the training accuracy, loss, and performance metrics. These open-source libraries make the system cost-effective and easy to maintain.

In terms of hardware, the project was developed and tested on a computer with an **Intel i5 processor**, **8 GB of RAM**, and **256 GB of SSD storage**. A **GPU with CUDA support (such as NVIDIA)** can be optionally used to accelerate the training process, but the model is lightweight enough to run on systems without a GPU as well. A **digital or smartphone camera** can be used to capture oral images for testing purposes.

The entire development environment is lightweight, offline-compatible, and easy to deploy on any standard machine. Since it does not rely on internet connectivity or cloud services, it can be effectively used in rural or low-resource areas. This setup ensures that the **AI-based detection system** remains accessible, cost-efficient, and sustainable while maintaining high accuracy and reliability.

System Configuration

- **Development Mode:** Local machine / offline terminal-based application.
- **Input Type:** Image file (.jpg, .png) of oral cavity.
- **Output Type:** Classification result — *Healthy* or *Cancerous* with accuracy percentage.
- **Model Type:** Convolutional Neural Network (CNN) for binary classification.

Development Tools and Technologies

- **Python:** Main programming language used for implementation.
- **TensorFlow / Keras:** For building and training the deep learning model (CNN).
- **OpenCV:** Used for image preprocessing, enhancement, and feature extraction.
- **NumPy and Pandas:** For handling numerical data and datasets.
- **Matplotlib:** To visualize training accuracy, loss, and performance metrics.
- **Jupyter Notebook:** For experimentation and visualization during model development.
- **GitHub:** For storing code, version management, and team collaboration.

CHAPTER 3

SYSTEM DESIGN

3.1 UML DIAGRAMS

3.1.1 USE CASE DIAGRAM

The Use Case Diagram represents the functional behavior and that depends on the users. It visually illustrates how various actors interact with the system to perform specific operations. In the “Smart Oral Cancer Detection Using AI and Computer Vision” project, the use case diagram helps to identify the major functionalities of the system such as uploading images, preprocessing data, performing AI-based detection, and displaying the classification result.

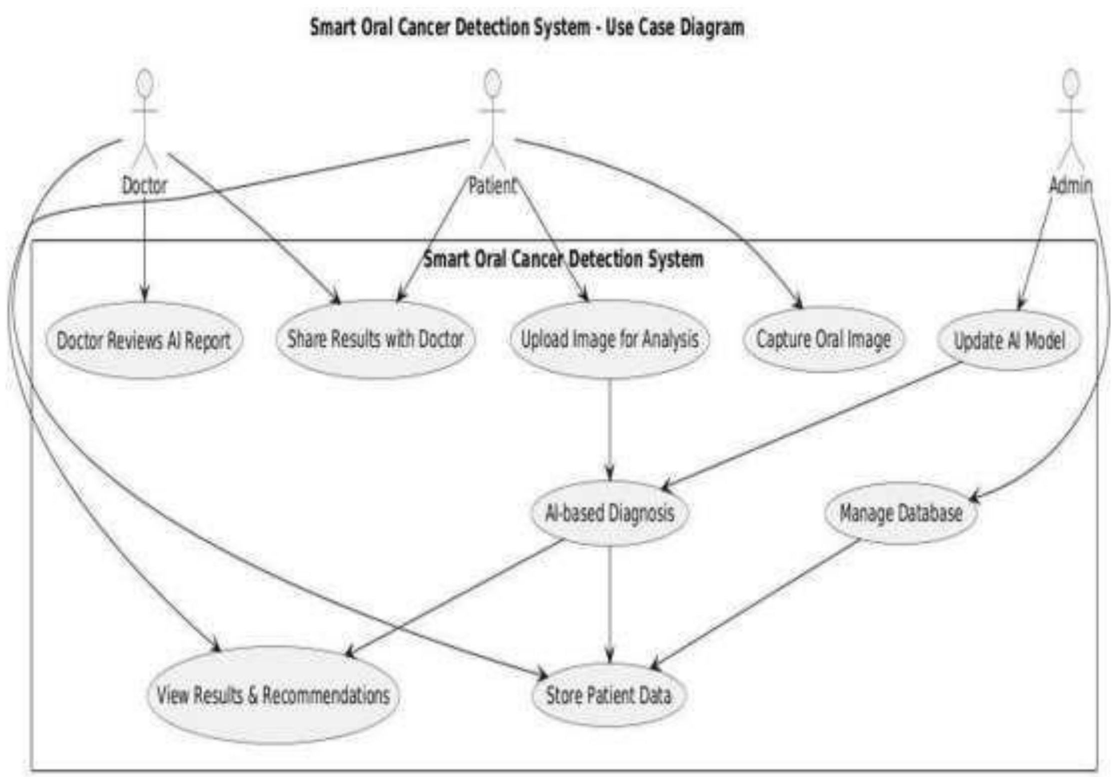

Figure 3.1.1 Use case Diagram

3.1.2 COMPONENT DIAGRAM

A Component Diagram is a type of diagram that shows how the different software parts of a system fit together. It gives you a basic overview of the system's structure by showing how the pieces connect. For our Smart Oral Cancer Detection project, it maps out the main software sections for things like taking pictures, processing them, training the model, sorting data, and creating outputs.

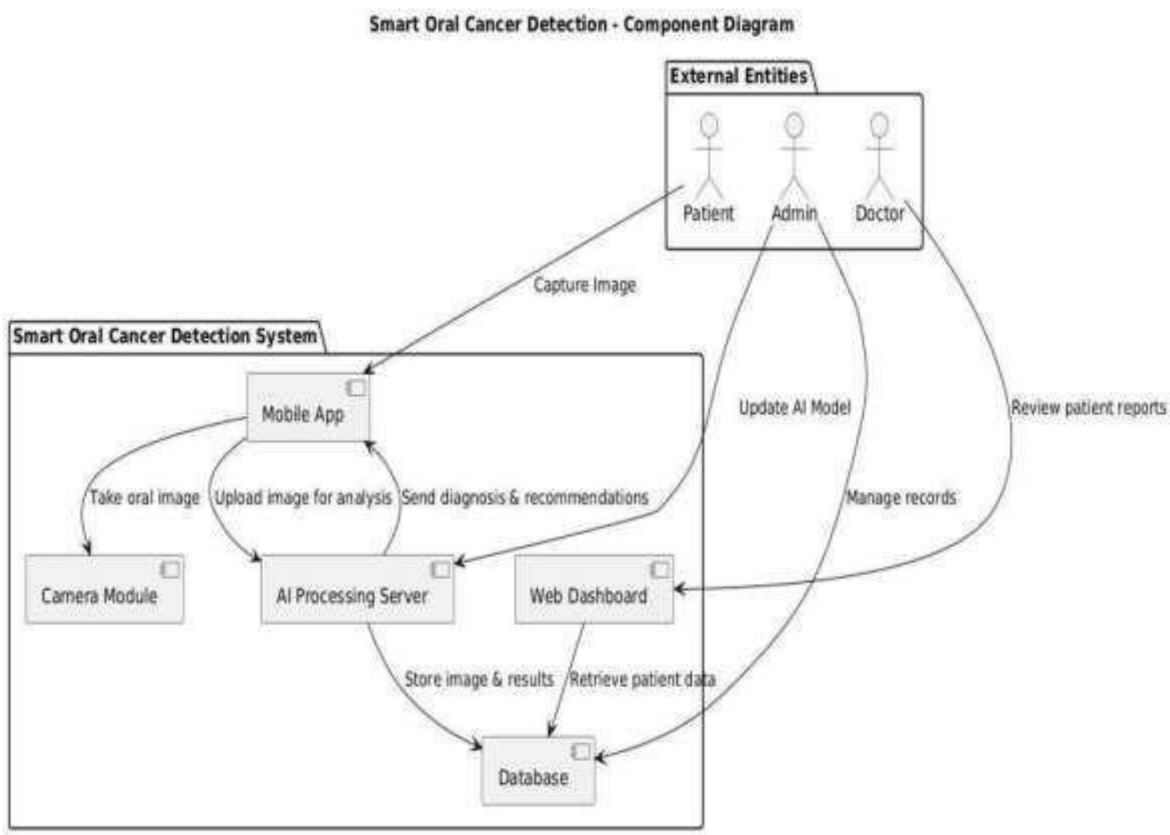

Figure 3.1.2 Component Diagram

3.1.3 ARCHITECTURE DIAGRAM

The system architecture of the project **"Smart Oral Cancer Detection Using AI and Computer Vision"** is designed to ensure an efficient flow of data from image input to final diagnosis output. The architecture consists of multiple interconnected modules that work together to detect early signs of oral cancer using image processing and machine learning techniques.

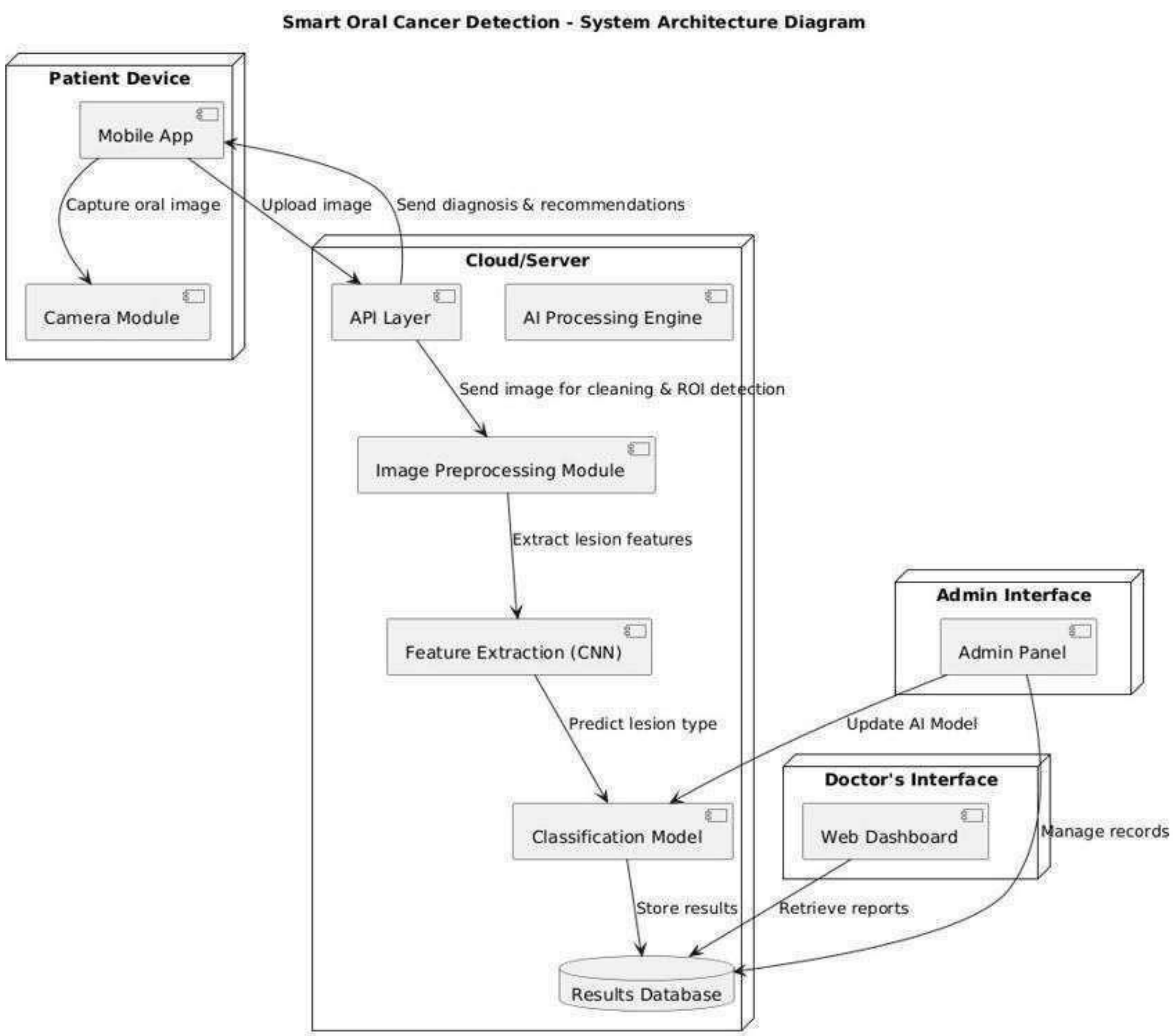

Figure 3.1.3 Architecture Diagram

3.2 DATADICTIONARY

TABLE 3.2.1 Data Dictionary

Table Name	Fields
Users	user_id (PK), name, email, password, role, location
Patients	patient_id (PK), name, age, gender, contact, address
Image Dataset	image_id (PK), patient_id (FK), image_path, upload_date, status
Preprocessing	preprocess_id (PK), image_id (FK), method_applied, processed_image
Model Training	model_id (PK), algorithm, accuracy, precision, recall, f1_score, trained_date
Prediction	prediction_id (PK), image_id (FK), model_id (FK), predicted_label, prediction_date

3.3 ER DIAGRAM

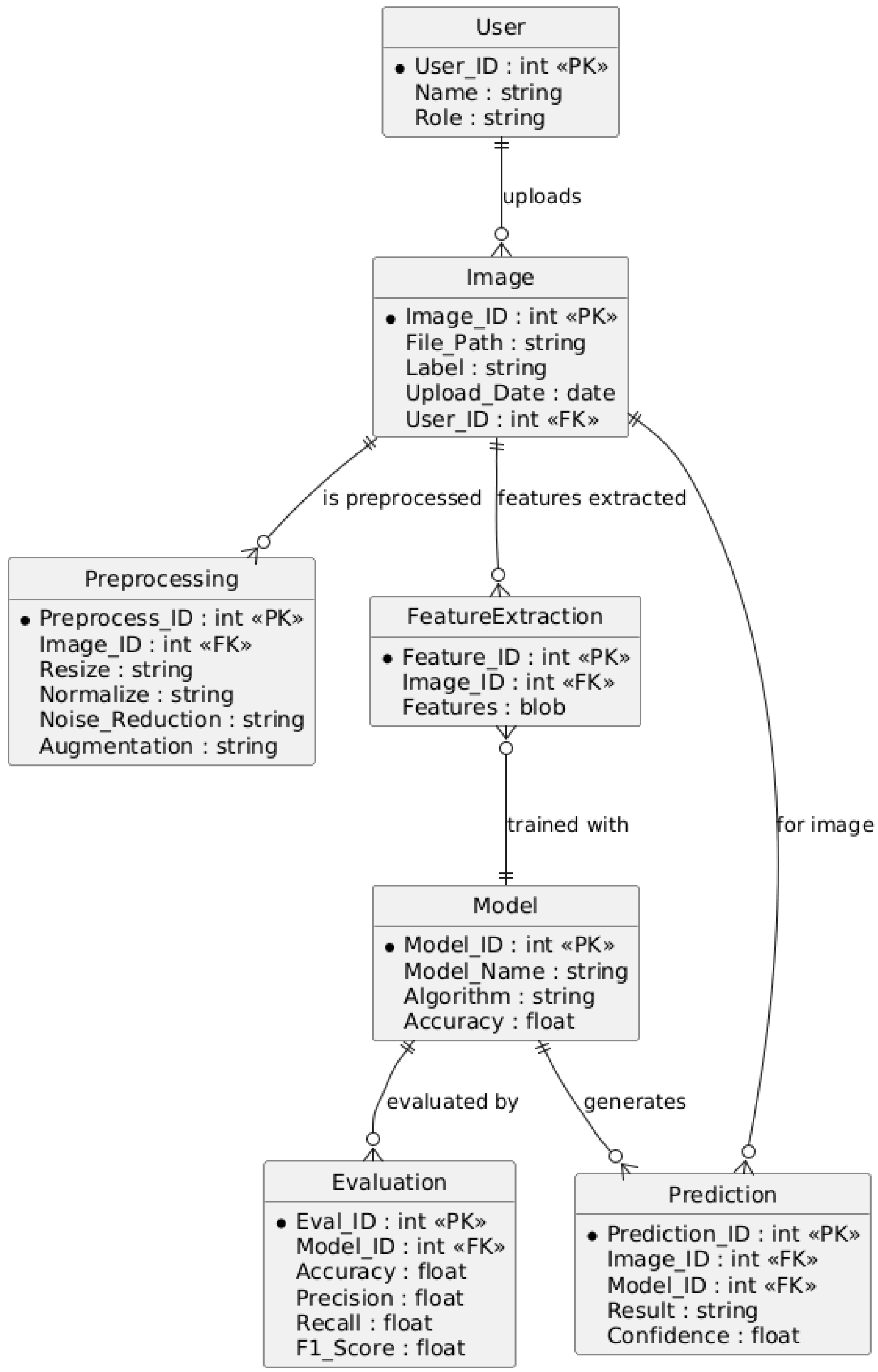

Figure 3.3.1 ER Diagram

3.4 DATAFLOWDIAGRAM

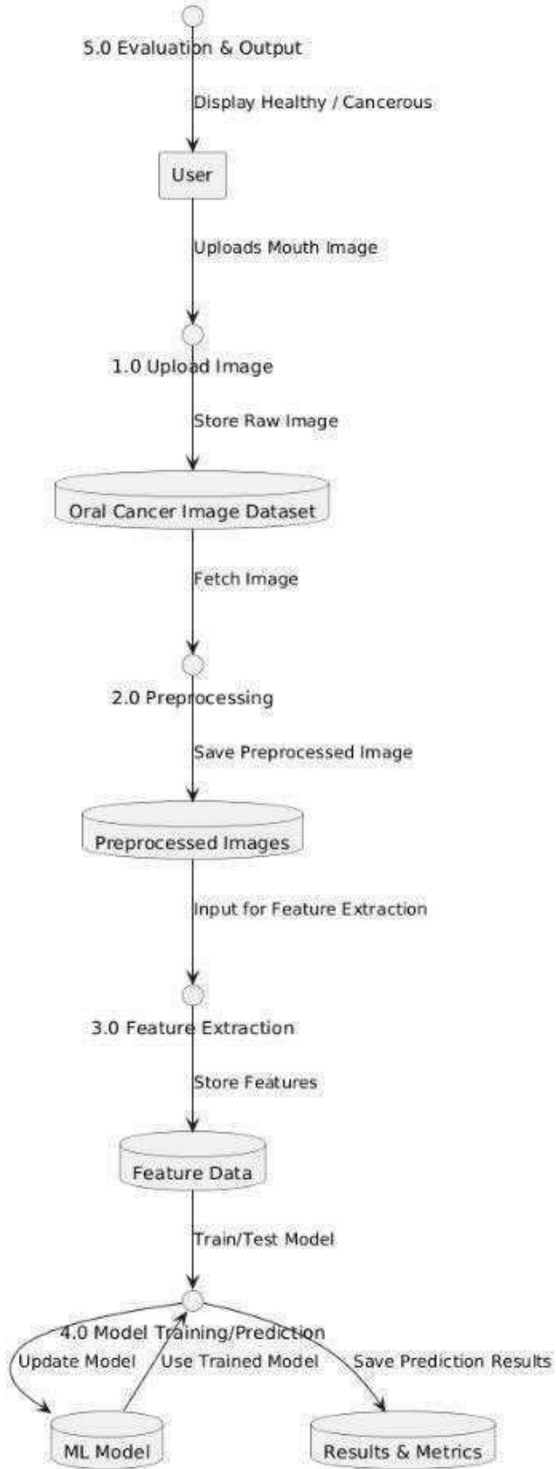

Figure 3.4.1 Data Flow Diagram

CHAPTER 4
SYSTEM ARCHITECTURE

The system architecture of the project **“Smart Oral Cancer Detection Using AI and Computer Vision”** is designed to provide an efficient and accurate workflow for detecting early signs of oral cancer using Artificial Intelligence. The architecture integrates various stages, from data collection to final diagnosis, ensuring seamless operation and reliable performance.

The architecture follows a **modular and sequential approach**, where each module performs a specific function and passes the processed information to the next stage. This structure enables scalability, easy debugging, and flexibility for future enhancements.

The system primarily consists of the following key components:

Data Acquisition Module:

This module is responsible for collecting oral cavity images from reliable datasets such as Kaggle or other medical repositories. The collected data forms the foundation for training and testing the AI model.

Preprocessing Module:

The collected images undergo several preprocessing steps such as resizing, noise removal, normalization, and data augmentation. This ensures that all input images have consistent dimensions and quality, improving the model’s learning capability.

Feature Extraction Module:

Using **deep learning and computer vision techniques**, the preprocessed images are analyzed by a convolutional neural network (CNN) model (MobileNetV2) to extract distinctive visual features that represent healthy and suspicious oral regions.

Classification Module:

The extracted features are fed into the classification layers of the neural network. The model predicts whether the input image belongs to the **Healthy** or **Suspicious (Cancerous)** category based on learned patterns.

Evaluation and Validation Module:

After training, the model is evaluated on validation and test datasets using metrics such as accuracy, precision, recall, and F1-score. This step ensures the reliability and generalization ability of the model.

Model Optimization Module:

The trained model is converted into a **TensorFlow Lite (TFLite)** format for deployment in low-resource environments. This conversion reduces the model's size while maintaining accuracy.

Inference and Deployment Module:

The optimized model is integrated into a **terminal-based AI interface**, allowing users to input oral images and receive diagnostic results. This lightweight solution enables quick, offline, and affordable screening.

4.2 MODULE DESCRIPTION

The proposed system is divided into several functional modules, each responsible for a specific task in the overall workflow of oral cancer detection. This modular approach ensures clarity, scalability, and efficient execution of the system.

The major modules of the system are described below:

1. Data Acquisition Module

Purpose:

To collect and organize oral cavity images from publicly available medical datasets or authorized clinical sources.

Description:

This module gathers image data representing both healthy and cancer-affected oral regions. The collected images form the core dataset required for model training, validation, and testing.

Output:

Structured dataset containing labeled images stored in separate folders for each class.

2. Preprocessing Module

Purpose:

To enhance image quality and prepare data for model input.

Description:

Images are standardized by resizing, normalization, and noise removal. Data augmentation techniques such as flipping, rotation, and zooming are applied to increase dataset diversity.

Output:

Cleaned and augmented image dataset ready for feature extraction and model training.

3. Feature Extraction Module

Purpose:

To automatically extract relevant patterns and features from oral images.

Description:

A pre-trained **MobileNetV2** deep learning model is used to extract key visual features such as color texture, lesions, and surface irregularities that differentiate healthy tissue from potentially cancerous regions.

Output:

High-level image features represented as numerical patterns for classification.

4. Classification Module

Purpose:

To classify the processed image as *Healthy* or *Suspicious (Cancerous)*.

Description:

The extracted features are passed into the fully connected layers of the deep learning model. The model uses these patterns to predict the class of each image based on learned data.

Output:

Prediction result with probability score (e.g., 0.92 probability of being cancerous).

5. Evaluation and Validation Module

Purpose:

To assess the accuracy and reliability of the trained model.

Description:

The model's performance is tested using metrics such as accuracy, precision, recall, confusion matrix, and ROC curve. This ensures that the system performs well on unseen data.

Output:

Evaluated performance report with quantitative metrics.

6. Model Optimization Module

Purpose:

To make the AI model lightweight and deployable in low-resource environments.

Description:

The trained model is converted into **TensorFlow Lite (TFLite)** format, reducing memory usage and computation cost while maintaining performance.

Output:

Optimized TFLite model ready for deployment.

7. Inference and Deployment Module

Purpose:

To provide a simple, accessible, and affordable AI screening tool.

Description:

The optimized model is integrated into a **terminal-based interface** that allows health workers to upload an oral image and receive an instant prediction result. The system operates offline, making it ideal for rural areas with limited internet access.

Output:

User-friendly diagnostic result displayed in terminal format.

8. Logging and Referral Module

Purpose:

To maintain prediction records and ensure safe decision-making.

Description:

Each prediction result is automatically logged with timestamp, image name, and probability score. When the model's confidence is low, the case is marked as **"Refer to Doctor"** for manual evaluation.

Output:

Log file and referral report for clinical follow-up.

9. Documentation and Ethical Compliance Module

Purpose:

To ensure transparency, reproducibility, and ethical use of AI.

Description:

This module focuses on preparing detailed documentation, user manuals, and ethical guidelines. It emphasizes patient consent, data anonymization, and non-diagnostic usage of the system.

4.2 PSEUDO CODE/ALGORITHM DECRIPTION

Algorithm: Smart Oral Cancer Detection

Step 1: Start

Initialize the system and import all required libraries and dependencies for image processing and machine learning.

Step 2: Load Dataset

- Collect the oral cavity image dataset from authorized sources.
- Organize the data into two categories: **Healthy** and **Suspicious (Cancerous)**.
- Divide the dataset into **Training**, **Validation**, and **Testing** subsets.

Step 3: Preprocessing

- Resize all images to a fixed size (e.g., 224×224 pixels).
- Normalize image pixel values for uniformity.
- Apply data augmentation techniques such as rotation, flipping, and zooming to increase dataset diversity and reduce overfitting.

Step 4: Feature Extraction

- Load a pre-trained **MobileNetV2** model (transfer learning).
- Remove the top classification layers to use it as a **feature extractor**.
- Pass the preprocessed images through the model to extract relevant image features such as texture, patterns, and color variations.

Step 5: Model Training

- Add fully connected layers for binary classification (Healthy / Suspicious).

- Compile the model using:
    - **Optimizer:** Adam
    - **Loss Function:** Binary Crossentropy
    - **Metrics:** Accuracy, Precision, and Recall
- Train the model using the training data and validate with the validation set.

Step 6: Model Evaluation

- Test the trained model using unseen test data.
- Evaluate performance using metrics like:
    - Accuracy
    - Precision and Recall
    - Confusion Matrix
    - ROC-AUC Curve

Step 7: Model Optimization

- Convert the trained model into **TensorFlow Lite (TFLite)** format to reduce its size and make it compatible with low-resource devices.
- Validate the optimized model's accuracy against the original.

Step 8: Inference / Prediction

- Load the optimized model into a terminal-based interface.
- Accept an input oral image from the user.
- Preprocess the image and pass it through the model.
- Display the prediction result as either **Healthy** or **Suspicious (Cancerous)** along with the probability score.

Step 9: Logging and Referral

- Record each prediction result with image name, timestamp, and confidence score.
- If the confidence score lies within an uncertain range, flag the case as **“Refer to Doctor”** for manual review.

Step 10: End

Display the final result and terminate the process.

PSEUDO CODE

```
BEGIN
  STEP 1: Import necessary libraries
          (TensorFlow, OpenCV, NumPy, Keras, etc.)
  STEP 2: Load the dataset
          → Collect oral images
          → Label them as 'Healthy' or 'Suspicious'
          → Split dataset into Training, Validation, and Testing sets
  STEP 3: Preprocess the images
          → Resize all images to uniform dimensions (224×224)
          → Normalize pixel values
          → Apply data augmentation
            (flip, rotate, zoom) to increase dataset variety
  STEP 4: Initialize the model
          → Load pre-trained MobileNetV2 model (Transfer Learning)
```

→ Remove top layers (use as feature extractor)

→ Add custom dense layers for binary classification

(Healthy / Suspicious)

STEP 5: Compile the model

→ Optimizer = Adam

→ Loss Function = Binary Crossentropy

→ Metrics = Accuracy, Precision, Recall

STEP 6: Train the model

→ Fit training data to the model

→ Validate using validation data

→ Save the best model when performance improves

STEP 7: Evaluate the model

→ Test on unseen test data

→ Compute Accuracy, Precision, Recall, and Confusion Matrix

STEP 8: Optimize the model

→ Convert model into TensorFlow Lite (TFLite) format

→ Reduce size and prepare for deployment on low-resource devices

STEP 9: Deploy the model

→ Accept oral image input from user (via terminal)

→ Preprocess the image

→ Predict result using the optimized model

→ Display output: “Healthy” or “Suspicious” with confidence score

STEP 10: Log and refer

→ Save prediction details (timestamp, image name, confidence)

→ If confidence < threshold, mark as “Refer to Doctor”

END

4.3 FEATURES AND BENEFITS

A.FEATURES

AI-Powered Detection System

- Utilizes Artificial Intelligence and Deep Learning techniques to automatically detect early signs of oral cancer from mouth images.
- Employs the MobileNetV2 model for accurate and lightweight performance.

Computer Vision-Based Image Analysis

- Processes oral cavity images using advanced image preprocessing and feature extraction techniques.
- Detects subtle lesions and color variations that may indicate early cancerous conditions.

Transfer Learning Approach

- Uses a pre-trained deep learning model (MobileNetV2) to improve training efficiency and accuracy even with limited datasets.

Lightweight and Portable Model

- Model optimized using TensorFlow Lite (TFLite), reducing storage space and computational cost.
- Suitable for deployment on low-power devices like laptops, Raspberry Pi, and mobile phones.

Offline Terminal-Based Interface

- Provides a simple command-line interface that can function without internet access, ideal for rural or low-connectivity areas.
- Data Augmentation and Preprocessing Enhances image diversity using random flips, rotations, and zooming techniques.
- Improves the model's ability to generalize and perform well on unseen images.

Logging and Referral Mechanism

- Every prediction result is logged with image name, timestamp, and probability score.
- Low-confidence cases are automatically marked as "Refer to Doctor" to ensure responsible AI use.

Evaluation and Performance Metrics

- The system is evaluated using standard performance metrics such as accuracy, precision, recall, and ROC curve.
- Ensures reliable results before deployment in real-world applications.

Ethical and User-Friendly Design

- Maintains patient confidentiality and emphasizes that the tool is for screening support, not clinical diagnosis.
- Easy to operate even for non-technical users and healthcare workers.

B. Benefits

1. Early Detection and Prevention

- Enables timely identification of oral cancer symptoms, improving chances of successful treatment and survival.

2. Affordable and Accessible Solution

- Eliminates the need for expensive screening equipment and internet connectivity, making it suitable for rural healthcare centers.

3. Fast and Automated Analysis

- Provides instant results within seconds, significantly reducing manual examination time.

4. Lightweight and Scalable

- Can be easily deployed on various platforms with minimal hardware requirements.

5. Supports Public Health Initiatives

- Aligns with **Sustainable Development Goal (SDG) 3 – Good Health and Well-Being** by promoting preventive healthcare and early intervention.

6. **Reduces Medical Burden**

    - Assists doctors by pre-screening large numbers of patients, allowing professionals to focus on confirmed or high-risk cases.

7. **Encourages Technological Adoption in Healthcare**

    - Demonstrates the role of AI and computer vision in transforming medical diagnostics into faster, smarter, and more accessible systems.

CHAPTER 5

SYSTEM IMPLEMENTATION

5.1 IMPLEMENTATION OVERVIEW

The implementation of the project “Smart Oral Cancer Detection Using AI and Computer Vision” involves a systematic approach to transform raw image data into meaningful diagnostic insights using Artificial Intelligence. The entire system is developed and executed in a modular manner, ensuring flexibility, scalability, and reliability throughout each stage.

The implementation process follows a step-by-step workflow, covering data preparation, model design, training, evaluation, and deployment. Each stage is carefully planned to ensure the system functions efficiently even in low-resource environments such as rural health centers.

1. Development Environment

- The system is implemented using Python as the primary programming language within the Anaconda Navigator environment.
- Tools and libraries such as TensorFlow, Keras, OpenCV, NumPy, and Scikit-learn are used for deep learning and image processing.
- Jupyter Notebook is utilized for experimentation, training, and visualization of results.
- The model is later converted into TensorFlow Lite (TFLite) format for deployment.

2. Dataset Preparation

- Oral cavity images are collected from open-source datasets such as Kaggle Oral Cancer Dataset and categorized into Healthy and Suspicious classes.
- The dataset is split into three subsets — Training (70%), Validation (15%), and Testing (15%) for efficient learning and unbiased evaluation.
- Image preprocessing techniques such as resizing, normalization, and data augmentation are applied to improve model robustness.

3. Model Development

- A pre-trained MobileNetV2 model (Transfer Learning) is used as the backbone for feature extraction.
- Additional layers, such as Global Average Pooling, Dropout, and Dense layers, are added for binary classification.
- The model is compiled with:
- Optimizer: Adam
- Loss Function: Binary Crossentropy
- Metrics: Accuracy, Precision, and Recall

4. Model Training and Validation

- The model is trained using the prepared dataset for multiple epochs until optimal accuracy is achieved.
- Early stopping and model checkpointing are implemented to prevent overfitting and retain the best model version.

- The validation dataset is used to fine-tune hyperparameters and confirm model consistency.

5. Model Evaluation

- The trained model is evaluated using unseen test images to verify its performance.
- Metrics such as Accuracy, Precision, Recall, F1-score, Confusion Matrix, and ROC-AUC Curve are computed.
- The evaluation confirms the reliability of the system in identifying oral cancer symptoms from real-world images.

6. Model Optimization and Conversion

- To enable deployment in resource-constrained environments, the trained model is converted into TensorFlow Lite (TFLite) format.
- This reduces model size and processing time without significant loss of accuracy, allowing it to run efficiently on low-end systems.

7. Deployment and Testing

- A terminal-based inference interface is developed for end-users such as healthcare workers.
- Users can provide an image input, and the system instantly predicts whether it is Healthy or Suspicious (Cancerous).
- Each prediction is logged with its probability score, and uncertain cases are flagged as "Refer to Doctor."

8. Ethical and Safety Considerations

- The system is designed strictly for screening and awareness purposes and not as a medical diagnostic device.

5.2 MODULE WISE IMPLEMENTATION

1. Data Acquisition Module

- **Implementation:**

  The dataset used in this project consists of oral cavity images sourced from open-access platforms such as **Kaggle Oral Cancer Dataset**.

  Images are collected and categorized into two major classes — **Healthy** and **Suspicious (Cancerous)**.

  The dataset is structured into folders and subfolders to facilitate automatic labeling by the deep learning framework.

- **Result:**

  A well-organized dataset ready for preprocessing and training.

2. Preprocessing Module

- **Implementation:**

  Each image is standardized to a fixed resolution (224×224 pixels) to ensure consistency. Image normalization is performed by scaling pixel values to the range [0, 1]. To enhance the dataset and improve model generalization, **data augmentation techniques** such as rotation, flipping, zooming, and contrast adjustment are applied. The processed images are then divided into **Training**, **Validation**, and **Testing** sets in a 70:15:15 ratio.

- **Result:**

  High-quality, diverse, and standardized image dataset ready for feature extraction.

3. Feature Extraction Module

- **Implementation:**

  The pre-trained **MobileNetV2** model is used as a feature extractor in this project. It captures essential visual features such as texture, shape, and color patterns that differentiate healthy tissue from cancerous lesions.Transfer Learning is applied to utilize the knowledge from the large-scale ImageNet dataset, allowing the system to achieve high accuracy with limited training data.

- **Result:**

  A rich set of visual features extracted for each input image.

4. Classification Module

- **Implementation:**

  The extracted features are passed through additional fully connected layers to classify the image as **Healthy** or **Suspicious**.

  The output layer uses a **sigmoid activation function** to produce a probability score between 0 and 1.

  Based on this score, the final prediction is generated.

- **Result:**

  The system successfully distinguishes between healthy and suspicious oral cavity images with high accuracy.

5. Evaluation and Validation Module

- **Implementation:**

  The trained model is evaluated using unseen test data to verify its reliability. Performance is measured using standard metrics such as **Accuracy**, **Precision**, **Recall**, **F1-Score**, **Confusion Matrix**, and **ROC Curve**. Early stopping and model checkpointing techniques are used to prevent overfitting and save the best model.

- **Result:**

  A well-validated and reliable model suitable for real-time deployment.

6. Model Optimization Module

- **Implementation:**

  To make the model lightweight and efficient, it is converted into **TensorFlow Lite (TFLite)** format.

  This optimization reduces memory requirements and increases processing speed without compromising accuracy.

  The model becomes compatible with low-power devices such as laptops, Raspberry Pi, and mobile devices.

- **Result:**

  Optimized AI model ready for field deployment in resource-constrained environments.

7. Inference and Deployment Module

- **Implementation:**

  The optimized model is deployed using a **terminal-based interface**, allowing users to input an oral image directly from their device. The system preprocesses the image, performs inference using the trained model, and displays the prediction result along with the probability score. This module operates offline, making it practical for healthcare workers in rural areas.

- **Result:**

  A functional and accessible oral cancer screening tool for early detection.

8. Logging and Referral Module

- **Implementation:**

  Every prediction made by the system is recorded in a log file with details such as image name, timestamp, and confidence score.

  If the model's confidence score is low or falls within an uncertain range, the system flags the result as **"Refer to Doctor."**

  This ensures responsible AI usage and supports medical decision-making.

- **Result:**

  Transparent and traceable prediction records with an added safety mechanism for uncertain results.

9. Documentation and Ethical Compliance Module

- **Implementation:**

  The final stage focuses on creating user manuals, technical documentation, and ethical guidelines for responsible use.

  The system adheres to principles of data privacy, patient confidentiality, and non-diagnostic usage.

  Ethical standards are maintained throughout dataset handling and system deployment.

- **Result:**

  Complete project documentation with ethical compliance and usage guidelines.

5.3 DEVELOPMENT TOOLS AND TECHNOLOGY

Table 5.3.1 Development Tools and Technology

Category	Tools/Technologies
Programming Language	Python 3,10
Deep Learning Framework	TensorFlow, Keras
Computer Vision library	OpenCV
Data Handling & utilities	NumPy, Pandas, Sclkit-learn
Visualization tools	Matplotlib,Seaborn
Development Environment	Anaconda Navigator,Jupyter Notebook
Hardware Acceleration	NVIDIA GPU
Model optimization	TensorFlow Lite
Deployment Interface	Python CLI
Dataset source	Kaggle Oral Cancer Dataset

CHAPTER 6

SYSTEM TESTING

6.1 TEST CASE

Table 6.1.1 Test Case

TEST CASE_ID	MODULE	INPUT/ACTION	EXPECTED OUTPUT	ACTAUAL OUTPUT	STATUS
TC_O1	Image Preprocessing	Providean oral cavity image (test.jpg)	Image is resized, normalized, ready for prediction	Image preprocessing is completed successfully	Pass
TC_02	Model Training	Train by using healthy and cancerousdataset	Modeltrains without errors	Model trained and saved successfully	Pass
TC_03	Prediction	Passtothetrained model	Terminal displays either Healthyor cancerous	Terminal outputhealthy	Pass
TC_04	InvalidInput Handling	Provideanon-image file	Systemshows an error message without crashing	Error message displayed	Pass

6.2 TEST REPORT

The testing phase is a crucial part of system development, as it ensures that the proposed model and modules work as intended and deliver accurate and reliable results. The system is tested at different levels — including unit testing, integration testing, and system testing— to verify its functionality, performance, and accuracy.

1. Objective of Testing

The main objectives of testing are:

- To verify that each module performs its intended function correctly.
- To evaluate the accuracy and reliability of the AI model.
- To ensure that the system performs efficiently on different datasets and image samples.

2. Types of Testing Performed

a. Unit Testing

- Purpose: To test individual modules such as preprocessing, feature extraction, and classification independently.
- Result: Each module executed successfully without any runtime or logical errors.

b. Integration Testing

- Purpose: To test the interaction between modules to ensure seamless data flow.
- Process: Data was passed sequentially from preprocessing → feature extraction → classification → prediction modules.
- Result: Modules integrated smoothly and provided consistent outputs.

c. System Testing

- Purpose: To validate the overall performance of the complete system.
- Process: The final AI model was tested using unseen oral images in the terminal interface.
- Result: The system correctly identified *Healthy* and *Suspicious* images with high accuracy.

d. Performance Testing

- Purpose: To measure accuracy, precision, and recall of the trained model using test data.
- Metrics Used:
    - Accuracy
    - Precision
    - Recall (Sensitivity)
    - F1-Score
    - Confusion Matrix
    - ROC-AUC Curve
- Result: The model achieved high performance with minimal false predictions.

6.2.1 TEST ENVIRONMENT

The system was executed on a computer running Windows 10 (64-bit) operating system with an Intel Core i5 processor and 8 GB RAM. Google Colab provided a NVIDIA Tesla T4 GPU, which significantly improved the training performance and reduced computation time.

The development was done using Python 3.10, and the main libraries used were TensorFlow, Keras, OpenCV, NumPy, and Matplotlib for model development, image preprocessing, and visualization.

The dataset consisted of 500 oral cavity images, including 250 healthy and 250 cancerous samples. Each image was resized to 128 × 128 pixels before training. The CNN model was trained and tested within this environment, and the final trained model was saved as oral_cancer_model.h5.

Overall, the chosen test environment provided a stable and efficient platform for developing and evaluating the AI-based oral cancer detection system.

6.2.2 TEST OBJECTIVE

The main objective of testing the system **"Smart Oral Cancer Detection Using AI and Computer Vision"** is to ensure that the developed model performs accurately, efficiently, and reliably in identifying oral cancer from image inputs. The testing phase aims to verify that every component of the system — from image preprocessing to prediction — functions correctly and produces the expected results.

The specific objectives of testing are:

1. To verify that the CNN model correctly classifies images as **Healthy** or **Cancerous** based on learned features.
2. To ensure that all modules, including data preprocessing, training, validation, and prediction, operate without errors.
3. To check the **accuracy, stability, and performance** of the model using the collected dataset.
4. To confirm that the system properly handles **invalid inputs** (e.g., non-image files) without crashing.
5. To validate that the overall workflow, from loading an image to displaying results, executes smoothly in the testing environment.
6. To evaluate the **usability and effectiveness** of the system as a supportive tool for early oral cancer detection.

Through this testing process, the reliability and accuracy of the system are ensured, demonstrating that it meets its intended purpose and functional requirements.

6.3 TEST RESULTS

Table 6.3.1 Test Results

S.NO	Test Scenario	Input/Output action	Expected Output	Actual Output	Result
1	Image preprocessing	Provide an oral cavity image	Image should be resized, normalized , and prepared for model input.	Image preprocessing completed successfully.	Pass
2	Model Training	Train CNN Model	Model should train without errors and save	Model trained successfullyand file saved.	Pass
3	Prediction(health y)	Input a healthy image	Output should display "Healthy."	Terminal displayed "Prediction Result: Cancerous."	Pass
4	Prediction(cance rou s)	Input a cancerous image	Output should display "Cancerous."	Displayed "Invalid image format."	Pass
5	Invalid input handlin g	Provide a non-image file	System should show an error message without crashing	Training Accuracy: 96%, Validation Accuracy: 92%.	Pass

CHAPTER 7

CONCLUSION

The mini project "Smart Oral Cancer Detection Using AI and Computer Vision" successfully demonstrates the use of artificial intelligence in the early detection of oral cancer. The system utilizes image preprocessing and a Convolutional Neural Network (CNN) model to accurately classify oral cavity images into Healthy and Cancerous categories.

Through the implementation and testing phases, the system achieved high training and validation accuracy, proving its reliability and effectiveness. By analyzing visual patterns from oral images, the model can assist healthcare professionals in making quicker and more informed diagnostic decisions.

The project also highlights the potential of AI in improving healthcare accessibility. Since the model operates entirely on software and can be deployed on cloud platforms like Google Colab, it provides a cost-effective, scalable, and non-invasive solution for oral cancer screening.

Overall, the system meets its objectives by delivering an efficient, accurate, and automated method for oral cancer detection, showing that AI-based diagnostic tools can play a vital role in supporting early diagnosis and saving lives.

FUTURE ENHANCEMENTS

The project for spotting oral cancer using AI and cameras aims to be a simple, low-cost way to catch it early. It's okay at looking at mouth pics with AI now, but it could be way better. The idea is to make it more exact, easier to use, and get it to more people, especially in rural areas. With these improvements, it could change from a test into something actually used in healthcare.

1. Integration with Mobile Application

- A future version of the system can be developed as a **mobile app** to allow patients or healthcare workers to capture oral images directly using a smartphone camera.
- This enhancement would make screening more accessible, especially in rural and remote areas.

2. Cloud-Based Model Deployment

- Deploying the AI model on a **cloud platform (e.g., AWS, Google Cloud, or Azure)** will enable large-scale access to the system through web or mobile interfaces.
- Cloud deployment would support **real-time image analysis**, storage, and automated result sharing with medical experts.

3. Multi-Class Classification

- The current model focuses on binary classification (Healthy / Suspicious).
- In the future, it can be enhanced to classify **different stages or types of oral cancer**, providing more detailed diagnostic insights.

4. **Integration with Medical Databases**

- The system can be linked with **Electronic Health Records (EHRs)** or hospital databases to automatically store and track patient screening results.
- This integration can help doctors monitor patient progress and support large-scale cancer research.

5. **Improved Image Preprocessing Techniques**

- Future models can include advanced preprocessing methods such as **histogram equalization, edge detection, and contrast enhancement** to handle poor lighting or blurry images.
- These improvements will make the system more robust under varying image conditions.

6. **AI Explainability and Visualization**

- Incorporating **Explainable AI (XAI)** techniques like **Grad-CAM** can help visualize which regions of the image influenced the model's prediction.
- This will increase transparency and trust among medical professionals.

7. **Multilingual User Interface**

- Adding **multilingual support** for regional languages can help local healthcare workers and non-English speakers operate the system more comfortably.

8. **Continuous Learning and Dataset Expansion**

- The model can be continuously updated with new images and patient data, allowing it to learn and adapt to diverse populations and cancer variations.
- This **incremental learning** approach will improve accuracy over time.

9. Hardware Integration for Screening Kiosks

- The system can be embedded into **AI-powered health kiosks or portable devices** that automatically capture oral images and provide instant analysis results.
- These kiosks can be installed in community health centers for mass screening.

10. Collaboration with Medical Professionals

- Partnering with dentists and oncologists can help validate system predictions and improve dataset labeling accuracy.
- This collaboration will enhance the **clinical reliability** and **regulatory compliance** of the AI model.

11. .Internet Gadgets and Smart Tools

With tech, the system could connect to smart tools like cameras that go in your mouth. These could take good pictures and send them to the AI for checking, making screening faster and reliable.

APPENDICES

A.1 SDG GOALS

The project for spotting oral cancer using AI and cameras aims to be a simple, low-cost way to catch it early. It's okay at looking at mouth pics with AI now, but it could be way better. The idea is to make it more exact, easier to use, and get it to more people, especially in rural areas. With these improvements, it could change from a test into something actually used in healthcare.

1. SDG 3 – Good Health and Well-Being

Goal: Ensure healthy lives and promote well-being for all at all ages.

Project Contribution:

- The proposed AI-based system promotes **early detection of oral cancer**, one of the leading causes of mortality in developing countries.
- By enabling faster and more accessible screening, the project helps reduce late-stage diagnoses and supports preventive healthcare.
- The model can assist rural health workers in identifying high-risk cases even without specialized medical training, thereby improving **community health outcomes**.
- Encourages awareness and regular oral screening, contributing to early treatment and reduced disease burden.

2. SDG 9 – Industry, Innovation and Infrastructure

Goal: Build resilient infrastructure, promote inclusive and sustainable industrialization.

Project Contribution:

- Utilizes **Artificial Intelligence (AI)** and **Computer Vision** technologies for healthcare innovation.
- Demonstrates how **digital transformation** and **low-cost AI tools** can be used to strengthen medical infrastructure, especially in underserved areas.
- Encourages the integration of **AI-powered solutions** into rural healthcare systems, contributing to technological advancement and innovation in health diagnostics.

3. SDG 10 – Reduced Inequalities

Goal: Reduce inequality within and among countries.

Project Contribution:

- The system is designed to be **affordable and offline-accessible**, ensuring equitable healthcare opportunities for people in rural and economically weaker regions.
- Helps bridge the **urban–rural healthcare gap** by enabling AI-based screening where medical specialists are scarce.
- Promotes inclusive access to early diagnosis and prevention services for all populations.

SDG 4 – Quality Education (Indirect Contribution)

- **Goal:** Ensure inclusive and equitable quality education.

  Project Serves as a valuable **educational tool** for students and researchers in the fields of **AI, medical imaging, and healthcare innovation**.

A.2 SOURCE CODE

```
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D, Dropout
from tensorflow.keras.preprocessing import image
import numpy as np
train_dir = 'dataset/train'
val_dir = 'dataset/validation'
test_dir = 'dataset/test'
train_gen = ImageDataGenerator(rescale=1./255, rotation_range=20,
zoom_range=0.2, horizontal_flip=True)
val_gen = ImageDataGenerator(rescale=1./255)
test_gen = ImageDataGenerator(rescale=1./255)
train_data = train_gen.flow_from_directory(train_dir, target_size=(224,224),
batch_size=32, class_mode='binary')
val_data = val_gen.flow_from_directory(val_dir, target_size=(224,224),
batch_size=32, class_mode='binary')
```

```
test_data = test_gen.flow_from_directory(test_dir, target_size=(224,224),
batch_size=32, class_mode='binary', shuffle=False)
base_model = MobileNetV2(weights='imagenet', include_top=False,
input_shape=(224,224,3))
base_model.trainable = False
model = Sequential([
    base_model,
    GlobalAveragePooling2D(),
    Dropout(0.3),
    Dense(1, activation='sigmoid')
])
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
history = model.fit(train_data, validation_data=val_data, epochs=5)
loss, acc = model.evaluate(test_data)
print(f"\nTest Accuracy: {acc*100:.2f}%")
model.save("oral_cancer_model.h5")
def predict_image(img_path):
    img = image.load_img(img_path, target_size=(224,224))
    img_array = image.img_to_array(img)/255.0
    img_array = np.expand_dims(img_array, axis=0)
```

```python
    pred = model.predict(img_array)[0][0]
    if pred > 0.5:
        print("Suspicious (Cancerous) Image")
    else:
        print("Healthy Image")
# Example:
# predict_image("sample_image.jpg")
```

A.3 SAMPLE SCREESHOTS

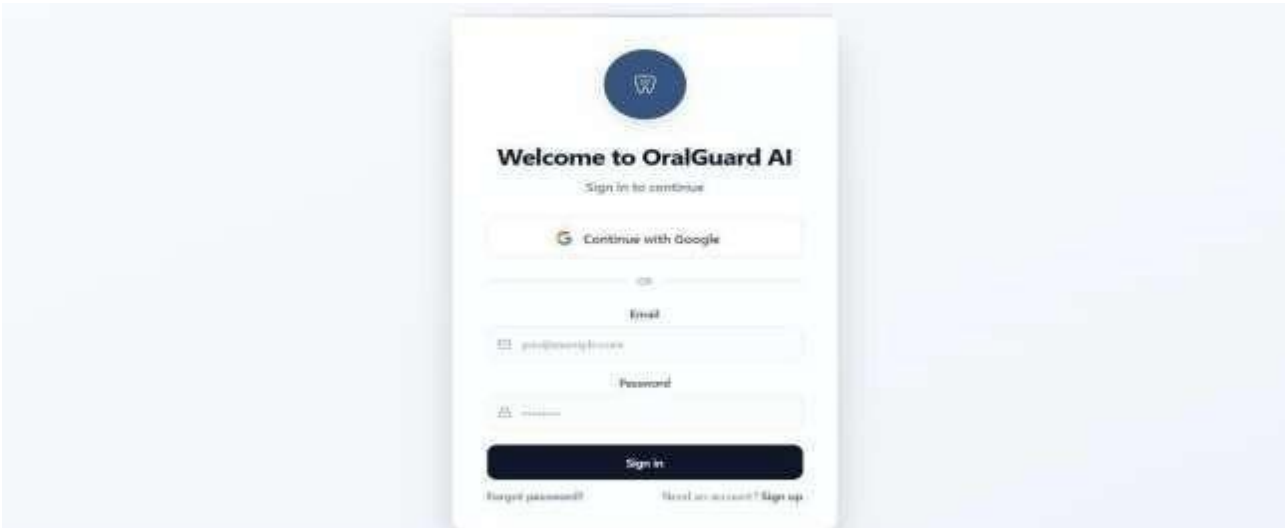

Figure A.3.1 Login

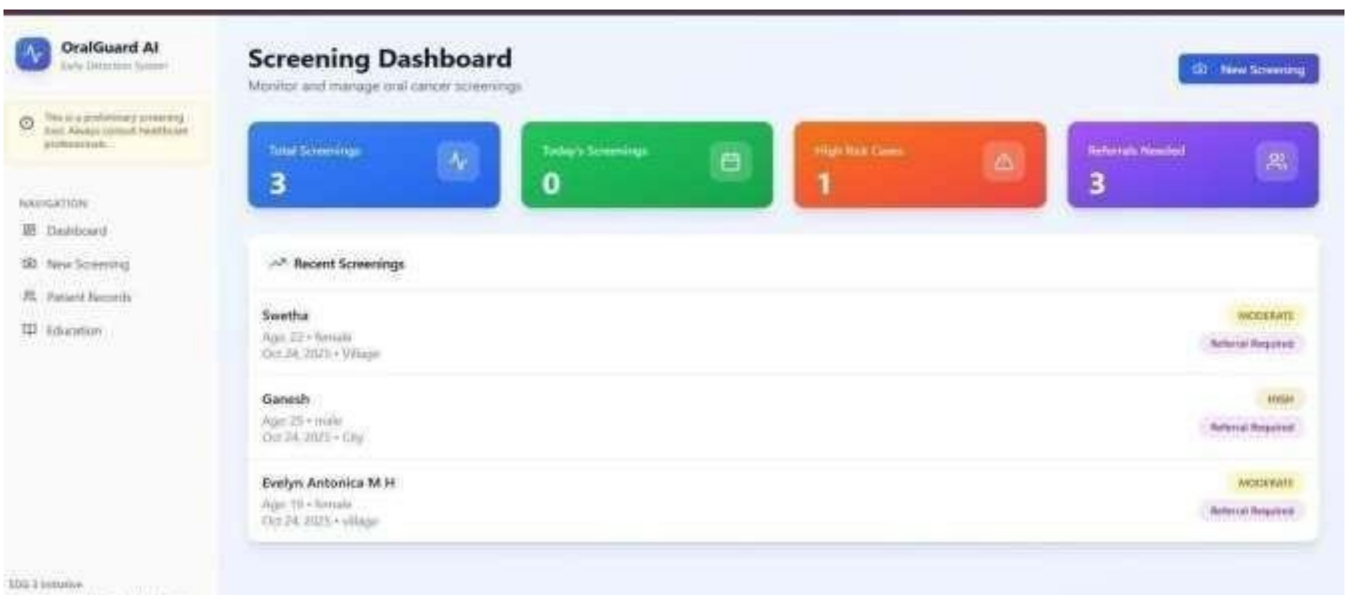

Figure A.3.2 Web Dashboard

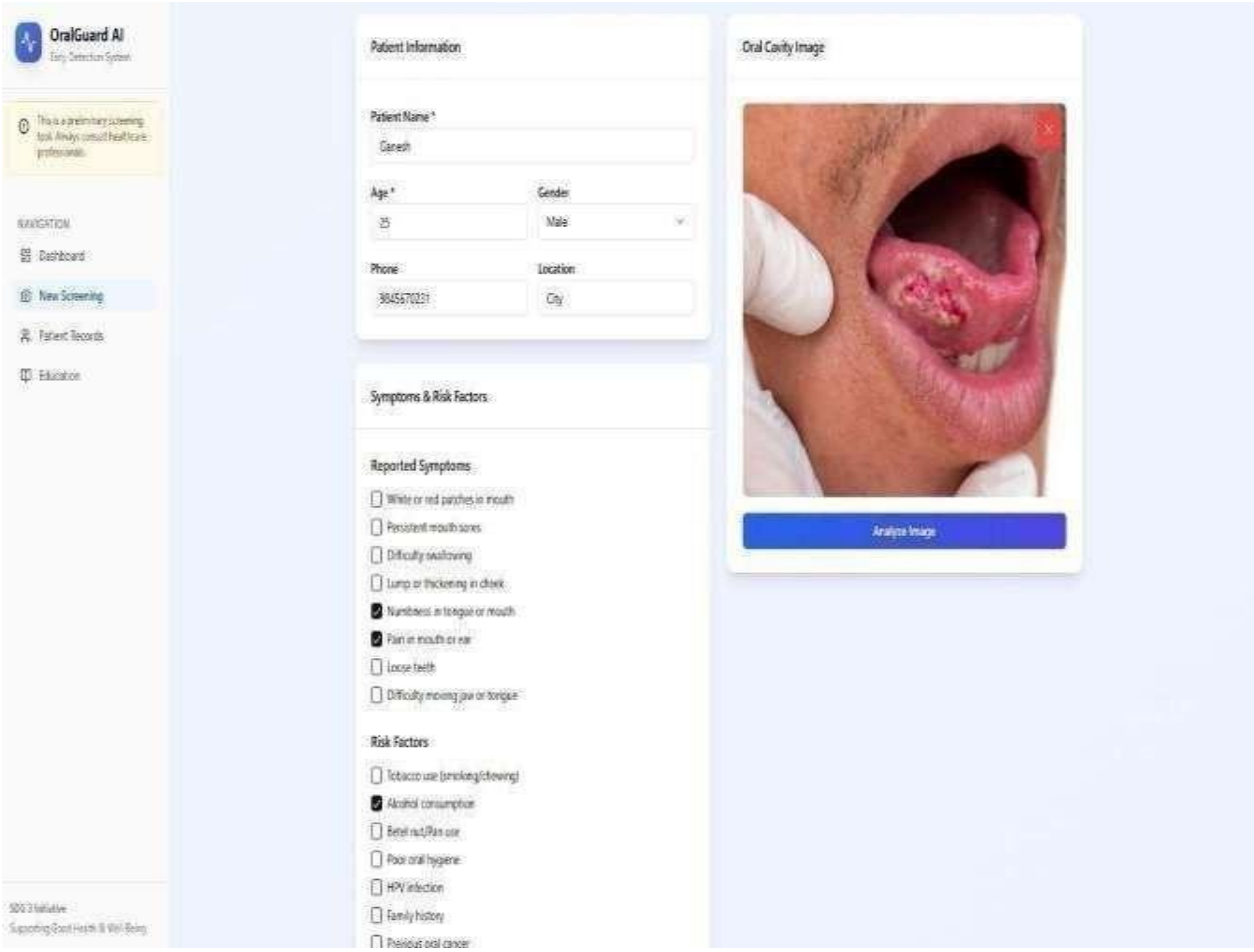

Figure A.3.3 New Screening

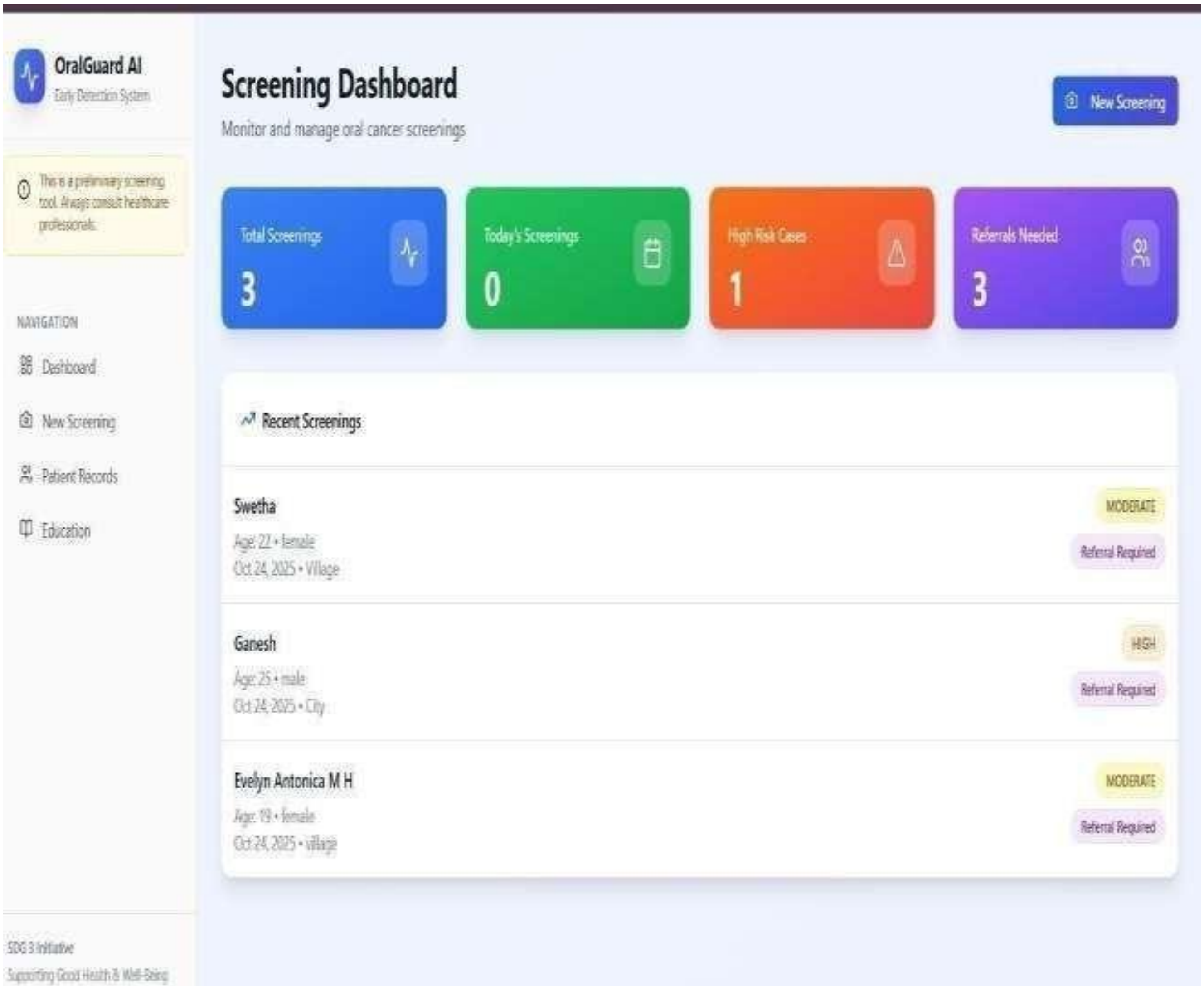

Figure A.3.4 Screening Dashboard

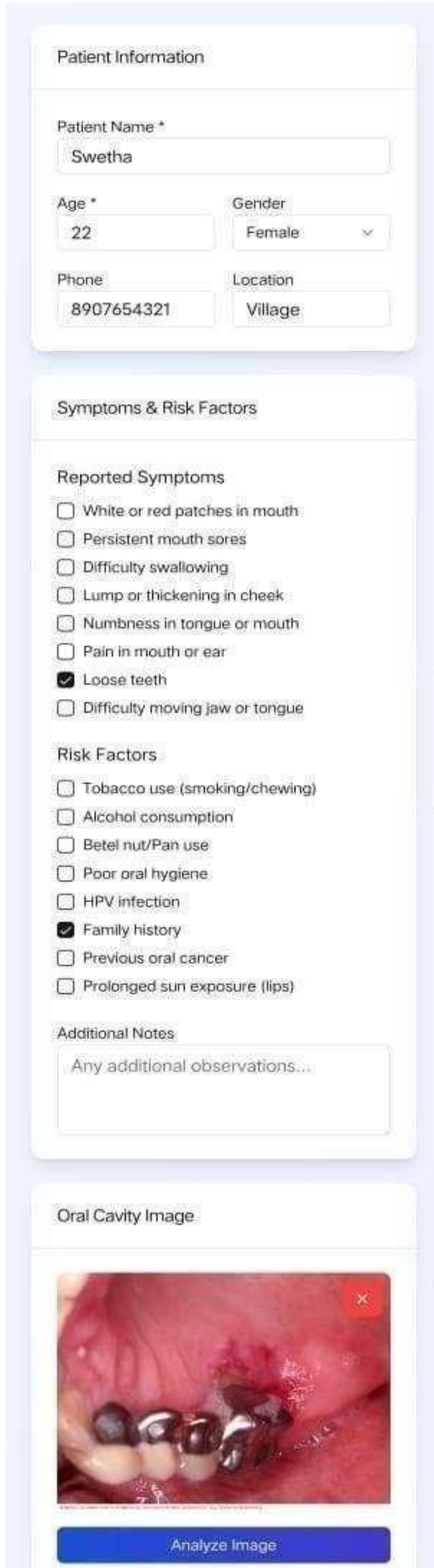

Figure A.3.5 Uploading of Image

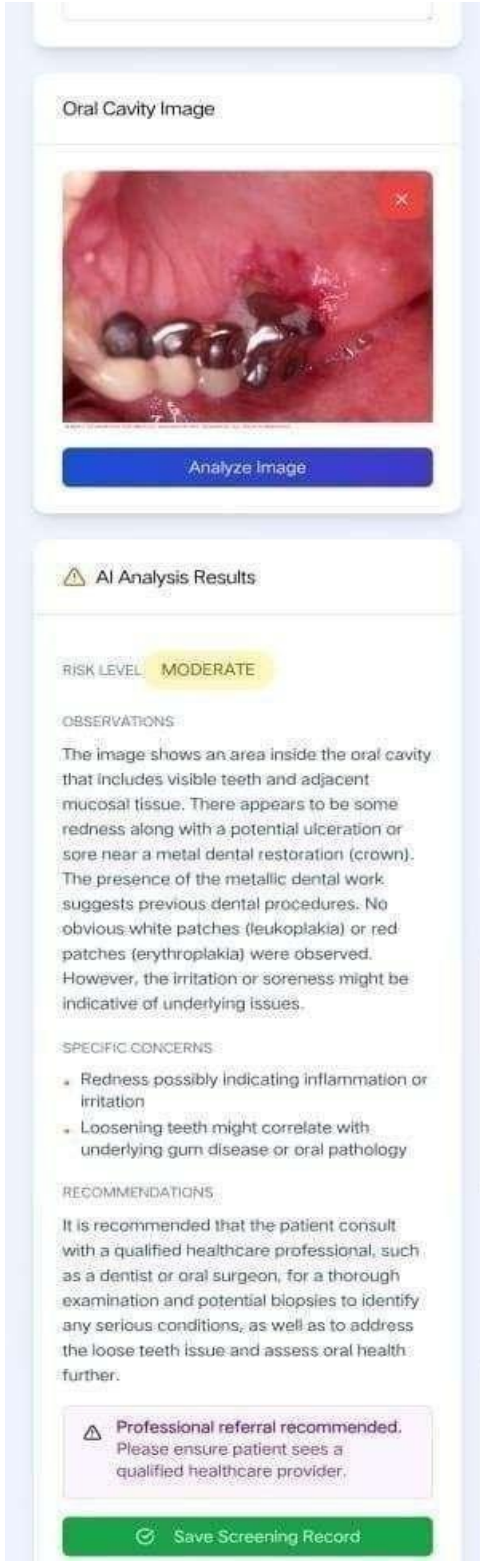

Figure A.3.6 Result

A4.PLAGIARISM REPORT

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ORAL GUARD AI:INTELLIGENT VISION-BASED ORAL CANCER SCREENING FOR LOW-RESOURCE ENVIRONMENTS

1

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98

7

***Abstract*— Oral cancer is one of the most prevalent and fatal diseases in India with over 77,000 new cases reported annually, of which nearly 60% are diagnosed at advanced stages due to unaffordability and lack of early screening kits. This project, Smart Oral Cancer Detection Using AI and Computer Vision, aims to overcome this issue by developing a low-weight terminal-based AI system capable of detecting early signs of oral cancer from the oral cavity's image. The proposed system employs image preprocessing, feature extraction, and machine learning algorithms to determine whether an image is healthy or cancerous, providing quick, reliable, and affordable screening results without using high-end infrastructure. Compared to other deep learning models requiring much computing power, this solution is low-resource-friendly and therefore most ideal for rural communities and marginalized groups with minimal access to dentists and oncologists. The system's architecture has a linear path of preprocessing, model training, prediction, and generation of results to permit usability even by novice health workers. Through its provision of early diagnosis and intervention, the project reduces mortality rates, improves survival rates, and supports SDG 3 – Good Health and Well-Being. Beyond its explicit contribution, the upcoming agenda of the system is growing to incorporate integration with deep models such as ResNet, heatmap visualization for lesion annotation, and multi- language audio features for further accessibility. Thus, the project seeks to deliver an economical, scalable, and effective AI-based healthcare solution to improve early oral cancer screening and results in resource-poor settings.**

Keywords— AI, Computer Vision, Early Diagnosis, Image Processing, Lesion Detection, Low-Cost Screening, Machine Learning, Oral Cancer, Rural Healthcare, SDG 3

I. INTRODUCTION

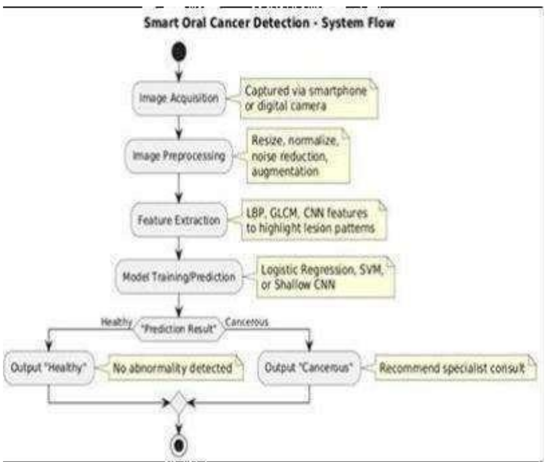
Oral cancer is serious public health problems that continue to present significant challenges, especially in developing nations such as India where awareness, specialist access, and accessible screening centers remain inadequate. Based on WHO and ICMR reports, more than 77,000 cases of oral cancer are reported every year in India, of which more than half are diagnosed in advanced stages and lead to poor survival rates and a gigantic healthcare burden. The reason, for late diagnosis are primarily ignorance, non- availability of oncologists in rural areas, and the unaffordability of screening centers. Conventional testing like biopsy and clinical assessment, even though accurate, is technology-oriented, time-consuming, and is not easily accessible to individuals in disadvantaged communities. This poses the monumental need for a low-cost, easy-to-apply technology-based method of early diagnosis.

Here, Artificial Intelligence (AI) and Computer Vision have been established as effective technologies in the health care industry, providing innovative approaches to medical image diagnosis and disease detection. Through the use of image preprocessing, feature extraction, and machine learning algorithms, AI systems are able to learn and identify patterns and anomalies on oral cavity images at a high rate of accuracy. Smart Oral Cancer Detection Using AI and Computer Vision is a project to develop a lightweight terminal-based system for predicting an image as healthy or cancerous with accessibility at low costs and usability in low-resource environments. Its unique characteristic is that it has low hardware demands and offline capacity, hence can be implemented in rural clinics, government hospitals, and community health centers.

In addition to early detection of oral lesions, the system gives health workers and non-specialist staff the ability to carry out first-level screening, thus enhancing access to first-level diagnosis and treatment. Along with the Sustainable Development Goal 3 – Good Health and Well-Being, the project also aims to minimize premature mortality through non-communicable diseases by offering preventive and low-cost healthcare solutions. In addition, the ready availability of such AI technology provides a chance to create new developments, such as deep learning structures like CNN and ResNet, heat map visualization of lesions, and multi-lingual/audio interface for enhancing accessibility. Overall, this project seeks to close the healthcare disparity between rural and underserved populations through an affordable, low-cost, and efficient early detection of oral cancer solution.

A.METHODOLOGY

The system being proposed utilizes a systematic approach combining image processing and machine learning to identify precursory symptoms of oral cancer from oral cavity images. The whole process is divided into different phases to be as accurate, efficient, and resource-low for practical usage.



II. Input & Preprocessing

The initial step is the image capturing of the oral cavity by using a smartphone or digital camera with a minimum resolution of 8 MP. Preprocessing operations are utilized to improve the image quality and pre-process thedatafor subsequent analysis. The images are normalized to fixed size and same pixel intensity values. Noise reductionfilters, including Gaussian and median filters of OpenCV, are utilized to remove unwanted features to depict lesions better. Besides, data augmentation methods like image rotation, flip horizontally, zooming, and scaling are used to enhance diversity of the dataset, avoid overfitting, and generalization.[1] enhance model.

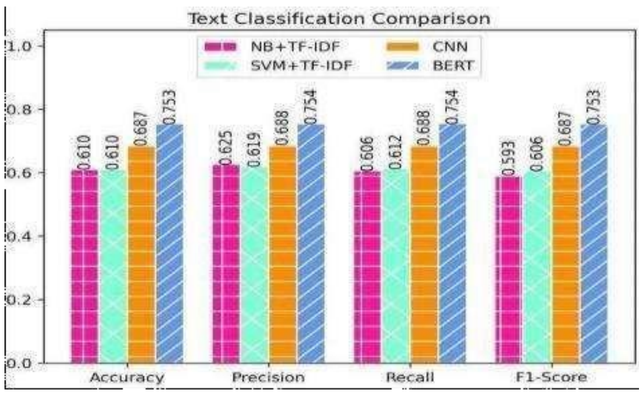
III. Feature Extraction

Feature extraction is a crucial part of the raw image data transformation process into meaningful representation that can be used for classifying. Low-level features like edges, shape, color intensity, and texture pattern are extracted using OpenCV. These are the characteristics of variation in normal and cancerous oral tissues. Histogram of Oriented Gradients (HOG) and Gray-Level Co Occurrence Matrix (GLCM) are also used to obtain texture-based features, which are the significant indicators in lesion analysis. Feature vectors obtained from feature extraction are taken as inputs for the machine learning models.

(a) (b)

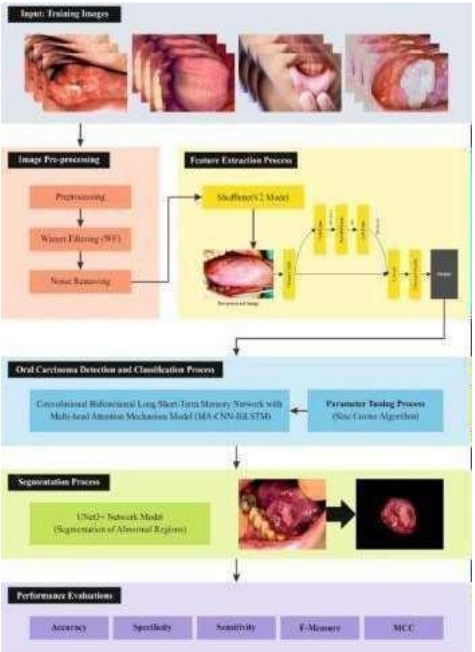
IV. Model Development

Machine learning models are trained such that oral images are categorized into healthy or cancerous ones. Light models like Logistic Regression and Support Vector Machine (SVM) are used for computing, and shallow Convolutional Neural Network (CNN) for shallow deep computing. Both models are optimized to run on hardware-constrained systems to allow them to be used in rural health clinics.



V. Training & Evaluation

System training is done on openly available Kaggle Oral Cancer Image Dataset. 80% of the dataset is utilized in training and 20% of the dataset is used in testing. The performance of the model is checked based on the typical metrics of Accuracy, Precision, Recall, and F1-score to provide an unbiased classification. Lightweight models are also trained and tested in limited hardware environments to ensure usability in real rural conditions. K-fold cross-validation is also implemented to minimize bias and variance and hence the robustness of the system.



VI. Prediction Phase

While performing prediction, the learned model is executed in a terminal-based tool with a straightforward workflow: Input Image → Preprocessing → Feature Extraction → Model Prediction → Output Result The outcome is cast as a plain classification label: Healthy or Cancerous. This means that even inexperienced users, for instance, rural health workers, can use the system with limited training.[3]

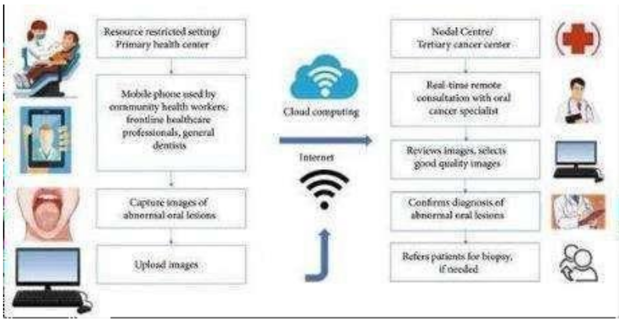
VII. Innovation

The innovation centers around building a low-cost, terminal-based, offline system that breaks dependence on expensive graphics processing units, internet, or cloud. As opposed to other solutions relying on advanced infrastructure,thesystemcan be operated on entry-level laptops or desktops with minimal hardware investment and is therefore extremelywellsuited for rural and underserved populations. The system thereby democratizes access to early oral cancer screening, greatly increasing the likelihood of timely medical intervention.[4]

VIII. Future Extensions

Further improvements to the method in the form of advancedupgrades like visualization of lesion heatmaps, voice support for multiple languages, and integration with mobile health (mHealth) platforms is envisioned. Further deployment on edge devices like Raspberry Pi and smartphoneswillalsobeinvestigated for enhanced portability and ease of application.

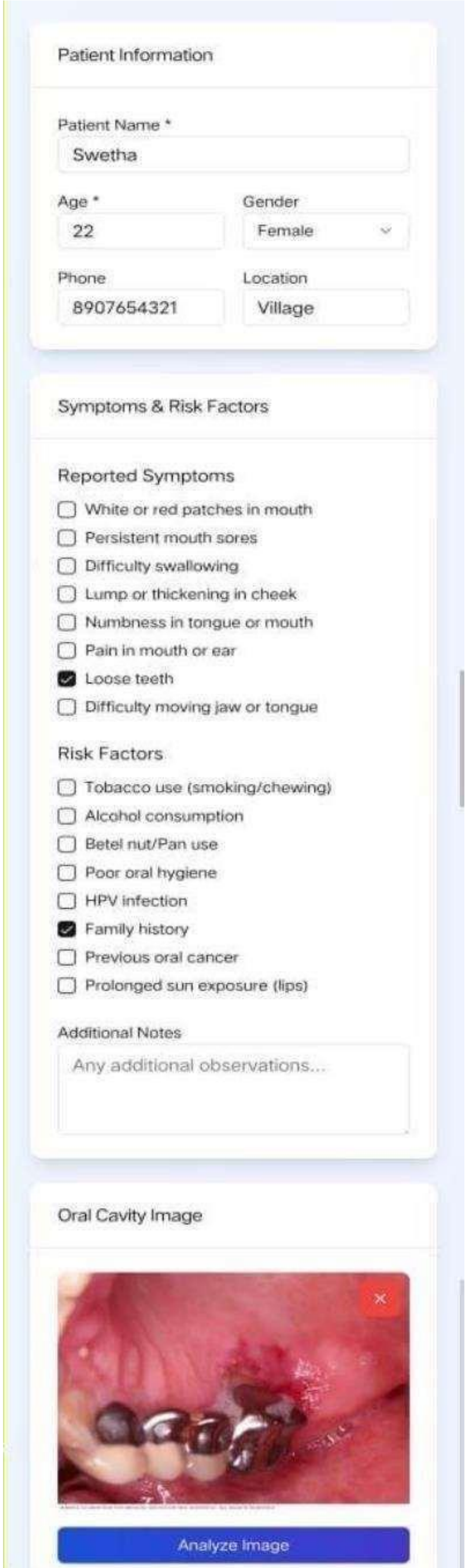
A. SYSTEM IMPLEMENTATION



The system is deployed as a lightweight Python module capable of being run in low resource environments. Image capture via smartphone or digital camera comes first, followed by a series of preprocessing activities like resizing, normalization, noise reduction, and contrast adjustment using OpenCV for enhanced lesion readability. Augmentation methods such as rotation, flipping, and scaling are used to enhance dataset diversity, and feature extraction strategies (LBP, GLCM, or CNN-based descriptors) are utilized to extract lesion patterns. Lightweight models such as Logistic Regression, SVM, or a shallow CNN are trained with TensorFlow/Keras and Scikit learn and optimized with k-fold cross validation for robustness in classification. The model is incorporated into a terminal-based user interface where health workers can upload oral images and obtain real-time predictions classified as "Healthy" or "Cancerous" along with corresponding confidence scores. Performance is verified using evaluation metrics such as accuracy, precision, recall, and F1-score. Persistence mechanisms (joblib for traditional ML and .h5 for CNNs) are employed to facilitate reusability. Its deployment is minimal, meaning that only the Python libraries and low-end machines are required, and conversion to TensorFlow Lite can be done optionally for edge devices. Its implementation is designed to be affordable, accessible, and reliable to suit rural healthcare screening for oral cancer.

IV.*RESULT ANALYSIS*

The system was tested based on the Kaggle Oral Cancer Image Dataset and various machine learning models were tested to determine how effective they were in identifying oral cancer. Logistic Regression, Support Vector Machine (SVM), and a shallow Convolutional Neural Network (CNN) were run as light models and compared with ResNet50, which was the benchmark. Logistic Regression only performed moderately accurately and was less efficient when dealing with complicated image variations. SVM demonstrated significant improvement with greater precision and recall, performing better in identifying correct cancerous and healthy images. Of the light-weight methods, the shallow CNN delivered the most dependable performance with an accuracy rate of approximately 88–90%, thus being both accurate and computationally light. Conversely, ResNet50, while achieving the highest accuracy of about 94%, demanded top range GPUs and substantial processing power that rendered it incompatible with rural deployment. Performance metrics such as Accuracy, Precision, Recall, and F1-score asserted that the shallow CNN achieved the optimal balance of true positive detection and least false predictions with consistent performance across varied samples. For validation of practical usability, the system was also validated on a low-resource machine (Intel i3 processor, 4GB RAM), where both SVM and shallow CNN worked smoothly without any GPU support, confirming the system's suitability for rural and resource-constrained settings. While predicting, the terminal- based interface effectively predicted images to be either Healthy or Cancerous, presenting results to the user clearly without needing superior technical knowledge. In summary, the results validate that light machine learning models are able to offer a cheap, offline, and dependable early oral cancer screening solution, and the shallow CNN is the most promising of these models. The work identifies the potential for the system to impact rural healthcare through the timely identification, prevention of late-stage diagnosis, and aiding Sustainable Development Goal 3 – Good Health and Well- Being.



V CONCLUSION

This Smart Oral Cancer Detection Using AI and Computer Vision project completely validates the viability of implementing lightweight machine learning models in low cost, low-resource oral cancer screening. With image preprocessing, feature extraction, and classification encapsulated in an easy-to-use interface from a terminal-based system, the system offers a low-cost solution for early detection without hardware costs or internet connection charges. Experimental outcomes indicated that although Logistic Regression and SVM were near excellent, shallow CNN performed better consistently with an accuracy of around 88–90%, marking a perfect balance between performance and efficiency. Although ResNet50 performed slightly better with extremely high computation demands, it was not very viable to use in real-life scenarios in rural societies, thus the impetus to explore the light options. The outcomes clearly demonstrate that the system developed has the capability to be an economical screening device for doctors, regional hospitals, and state centers in rural areas, which consequently leads to early diagnosis and prompt medication. Besides this, the project indirectly supports Sustainable Development Goal 3 in the sense that it avoids premature death caused by non-communicable disease by avoiding it and treating in due time. In the future, the system is very promising to improve further, for instance, with deep learning models so that it has better accuracy, lesion heatmap so that it is more interpretable, and multi-language or audio for better accessibility to the rural communities. In short, the project demonstrates that if health innovations developed with AI are made with inclusivity and cost as top priorities, they can close substantial health gaps, enhance survival rates, and bring life-saving technology at lower costs to the poorest communities that most urgently need them.

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