Oral Cancer Detection Using AI and Computer Vision

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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

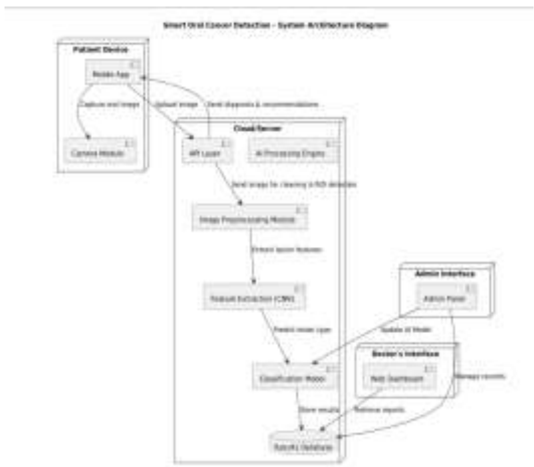
Oral cancer is one of the serious public health problems that continue to present significant challenges, especially in developing nations such as India where awareness, specialist access, and accessible screening centers remain inadequate. Based on WHO and ICMR reports, more than 77,000 new cases of 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 reasons 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.

III. 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.

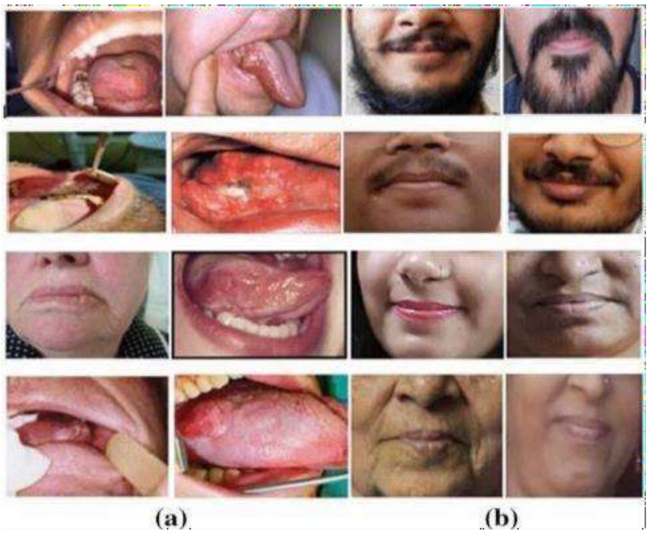


II. Input & Preprocessing

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.

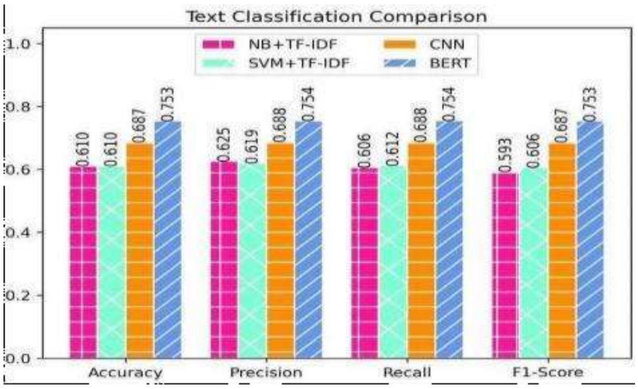
III. Feature Extraction

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.



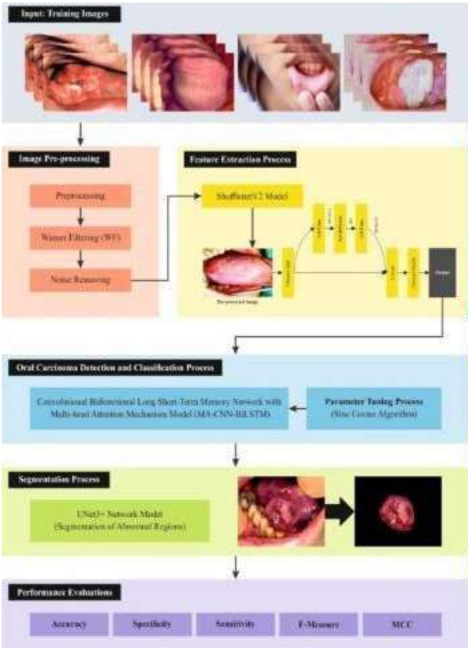
IV. Model Development

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]

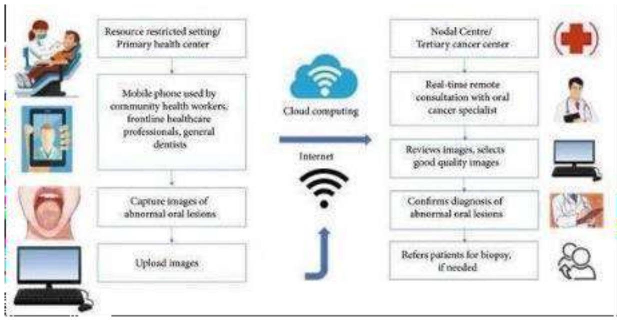
VII. Innovation

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.

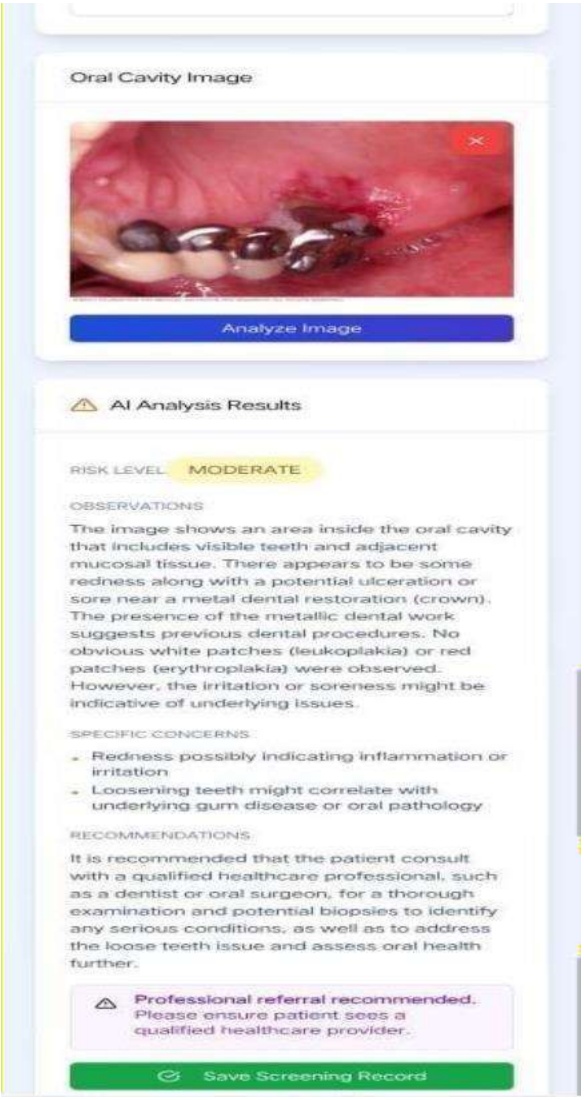
A. *SYSTEM IMPLEMENTATION*

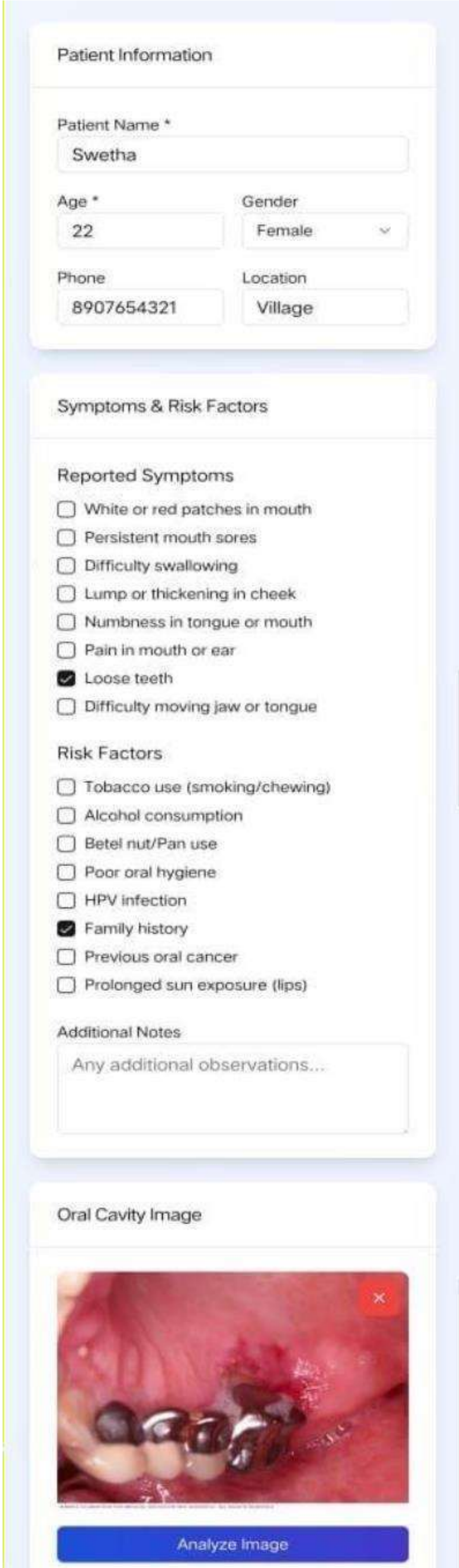


The system is deployed as a lightweight Python module capable of being run in low resource environments. Image capture via smartphone or digital camera comes first, followed by a series of preprocessing activities like resizing, normalization, noise reduction, and contrast adjustment using OpenCV for 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.R*ESULT 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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