IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 5, May 2026

DOI: 10.17148/IARJSET.2026.13545

ORAL CANCER DETECTION

Chirag R[1], Sujayeendra Rao[2]

PG Student, The National Institute of Engineering, Mysuru,

Visveswaraya Technological University, Belagavi, Karnataka, India[1]

Faculty, The National Institute of Engineering, Mysuru,

Visveswaraya Technological University, Belagavi, Karnataka, India[2]

Abstract: Oral cancer is one of the most common and life-threatening cancers worldwide, particularly in developing regions where tobacco consumption, alcohol usage, and poor oral hygiene are prevalent. Early detection of oral cancer significantly improves survival rates; however, conventional diagnostic methods rely heavily on clinical examination and biopsy procedures, which are invasive, time-consuming, and dependent on expert availability. This project presents an intelligent Oral Cancer Detection System using machine learning and deep learning techniques to assist in early screening. The proposed system employs a Convolutional Neural Network (CNN) for analyzing oral cavity images to classify them as cancerous or non-cancerous. In addition, a machine learning-based clinical prediction model evaluates patient risk factors such as age, tobacco usage, alcohol consumption, and the presence of oral lesions. By integrating image-based analysis with clinical data evaluation, the system enhances diagnostic reliability and decision support. The developed models are deployed using a Streamlit-based web application that allows users to upload oral images and enter clinical details for real-time prediction. Experimental results demonstrate that the image-based model achieves high classification accuracy, while the clinical model effectively supports risk assessment. The proposed system provides a non-invasive, cost effective, and user-friendly solution for preliminary oral cancer screening, aiming to support healthcare professionals and improve early detection outcomes.

Keywords: deep learning, oral cancer detection, oral cancer, risk factors, cancer remedies, hospitals suggested.

I. INTRODUCTION

Cancer ranks among the world's top ten causes of mortality, representing a significant public health challenge across developed and developing nations. Within this broad category, numerous cancer types exist, each with distinct characteristics and treatment approaches. Oral cancer occupies a particularly important position among cancers affecting the head and neck regions. The prevalence of oral cancer correlates strongly with specific behavioral and environmental factors. Regions where the consumption of tobacco and alcohol is high have seen an increase in the incidence of oral cancer. Additionally, betel nut chewing practices among certain populations increase the of succumbing to this disease. The combined impact of poor oral hygiene practices in at-risk communities adds to the multitude of contributing factors of this multifactorial disease process. Diagnostic Challenges and Opportunities Early detection significantly increases the of survival and decreases treatment costs. Unfortunately, diagnosing oral cancer presents a diagnostic complication. Traditional methods of screening are based primarily on visual examination with tissue being collected via biopsy and confirmation through the use of laboratory analysis that is both time-consuming and costly, putting a strain on patients. Artificial intelligence and deep learning is a technology that has opened new opportunities for diagnosing oral cancer. Convolutional neural networks (CNNs) are an example of a type of deep learning that can process medical images effectively as well as detect very subtle variations that may not be visible to the eye. Additionally, machine learning has effective at detecting risk factors for developing oral cancer among many other types of cancer.In the proposed research activity, development of an intelligent system for the diagnosis of oral cancer, integrating image-based deep learning techniques with data-based machine learning techniques would be done. In the proposed system, image processing tasks on the images of the oral cavity by using the CNN technique and risk factors for patients would be done by risk factor analysis on the basis of predictive models. This technology too can be developed for advancement as an application for the web service using Streamlit. The end-users shall also be able to upload photographs containing images inside the oral cavity. These would then be used for predictive purposes. The proposed system is expected to provide fast, contactless, cost-effective, and highly accessible predictive solution(s) regarding oral cancer diagnosis.

II. SCOPE OF THE LITERATURE SURVEY

The literature on oral cancer detection emphasizes deep learning advancements for accurate, field-ready classification amid data scarcity and real-world variability.[1] Payal Gulati et al. (2024) proposed a nano-modified electrochemical

DOI: 10.17148/IARJSET.2026.13545

immunosensor for the early detection of oral cancer biomarkers in the investigation, the determination of specific biomarkers such as CYFRA21-1, IL-8, and TP-53 by nano-enhanced screen-printed electrodes was targeted. The techniques involve modification of electrode surfaces, immobilization of antibodies, and estimation of electrochemical currents. The team confirmed their approach using standard laboratory methods, known as ELISA tests. Their results show the new technique is highly sensitive, successfully detecting In very low levels of the key biological markers.[2] Research by Aniket Balapure and colleagues (2024) presented a comprehensive review of point of-care testing (POCT) devices for oral cancer detection, with an emphasis on microfluidic and colorimetric technologies. This paper discusses a variety of technologies, both of which are being utilized in their current forms, such as microfluidic chip platforms, paper-based sensors, lateral flow methods, and colorimetric reaction techniques using nanoparticles. Unlike most reviews done, which are focused on a single point of accuracy for comparison, this review adopts a set of criteria based on REASSURED for reviewing these technologies. This corresponds to a need for a low-cost, quick diagnostic method especially useful in settings that do not possess an abundance of resources. It doesn't use machine learning in its application but recommends integrating biochemical POCT technology along with an image machine learning platform.[3] The uses of Deep Learning techniques in Oral Cancer detection and prognostics has been systematically reviewed by Kritsasith Warin & Siriwan Suebnukarn in the year 2024. It talks about the proliferation of models of Deep Learning prophets, from CNN models of classification to models such as DeepSurv, prognostics models They asserted that the overall sensitivity and specificity are 0.92, which is extremely high. It further continues to explore how transfer models have begun to gain importance. "The only problem with these models is they have Dept. of MCA, NIE, Mysuru 5 Oral cancer detection 2025-26 not been generally validated to be generalized." These results are highly applicable to transfer learning models in the area of diagnosis in images used in for oral cancer diagnosis[4] B. Goswami et al. (2024) proposed a machine learning-based approach for oral cancer classification using white-light images. The proposed study utilizes comprehensive color and texture extraction, multi-color space transformations, and feature selection methods, followed by the application of the LightGBM boost classifying technique. The proposed system achieved outstanding classification results with high accuracy, with values reaching 99.25% for binary classification and 98.88% for multi-class classification, validated using cross-validation and on separate testing datasets. The development of this thesis proved that the traditional machine learning algorithms can effectively and performing equally when integrated with engineered features. The proposed approach can be considered an excellent benchmark for designing efficient systems for the detection of oral cancer and indicates that includes traditional machine learning approaches with the embedding power of deep networks can lead to outstanding robustness and accuracy.

III. PROPOSED WORK

The proposed system introduces an intelligent oral cancer detection framework that integrates image-based deep learning with clinical (tabular) data analysis to support early and accurate diagnosis. The system based on the idea of using a Convolutional Neural Network as an efficient backbone for image analysis from the oral cavity to detect suspicious lesions, patterns, and other visual irregularities related to oral cancer. For increasing the diagnostic capability, the clinical properties of patient are taken into account, including age, tobacco use, alcohol use, habits of mouth, the duration of lesions, and any medicinal use, all processed through a tabular-based model developed on a machine learning platform. In this case, there is a strict process that includes image acquisition, image pre-processing, deep learning-based feature extraction, ingestion of clinical data, and ultimately a risk prediction model from model fusion. Hence, the amalgamation of both visual and clinical characteristics overcomes significant constraints that are normally encountered in both independent methods and thus provides a diagnosis which is more resistant and reliable. The developed models shall be deployed using a Streamlit-based web interface that shall enable doctors and healthcare professionals to upload their pictures and fill in details about their Patients to get real-time predictions of their models. The developed system would be non-invasive, cost-effective, and thus easily deployable within hospital setups in both urban and rural settings that are usually deprived of technological advancements. Thus, it would be easily deployable within hospital setups in both urban and rural settings that are usually deprived of technological advancements and easily deployable within hospital setups in both urban and rural settings that are often deprived of technological advancement. Thus, the system would be easily deployable within hospital setups in both urban and rural settings that are often at a loss for technological advancement and hence easily deployable within the setups of hospitals in both urban and rural settings that often reside deprived of technological advancement and hence easily deployable within the setups of hospitals in both urban and rural settings, which often face dearth of technological advancement and hence easily deployable within hospital setups in both urban and rural settings that often experience shortage of technological advancement and hence easily deployable within hospital setups in both urban and rural settings.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
Impact Factor 8.311 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 13, Issue 5, May 2026
DOI: 10.17148/IARJSET.2026.13545

IV. METHODOLOGY

This methodology details the development of an integrated oral cancer detection system utilizing a dual-pathway approach of CNNs for image analysis and machine learning for clinical data. The process begins with the acquisition and rigorous preprocessing of oral cavity images and patient records to ensure data normalization and noise reduction. Through exploratory data analysis and hypothesis testing, the system identifies key features that drive malignancy, evaluating model performance using metrics like precision, recall, and F1-score. To optimize diagnostic reliability, a decision-level fusion approach combines the visual insights from the CNN with the non-visual clinical evaluations. This unified model is deployed via a real-time Streamlit application, providing a non-invasive, accessible platform for automated oral cancer screening.

A. *Data Collection:* The system uses two types of data: oral cavity images and patient clinical data. Oral images representing normal and cancerous conditions are collected from publicly available medical datasets. Clinical data such as age, tobacco usage, alcohol consumption, oral habits, lesion duration, and medical history are also gathered to support risk factor analysis.

B. *Data Preprocessing:* The collected oral images are pre-processed to improve quality and consistency. This includes resizing images to a fixed dimension, normalization of pixel values, and noise reduction. Data augmentation techniques such as rotation, flipping, and brightness adjustment are applied to increase dataset diversity and reduce overfitting. Clinical data is cleaned from handling missing values, encoding categorical variables, and normalizing numerical attributes.

C. *Model Training:* The CNN model is trained using the preprocessed oral image dataset. Simultaneously, a machine learning model is trained on the clinical dataset to analyze patient risk factors. The training process involves divide the data into training, validation, testing sets to ensure unbiased learning and performance evaluation.

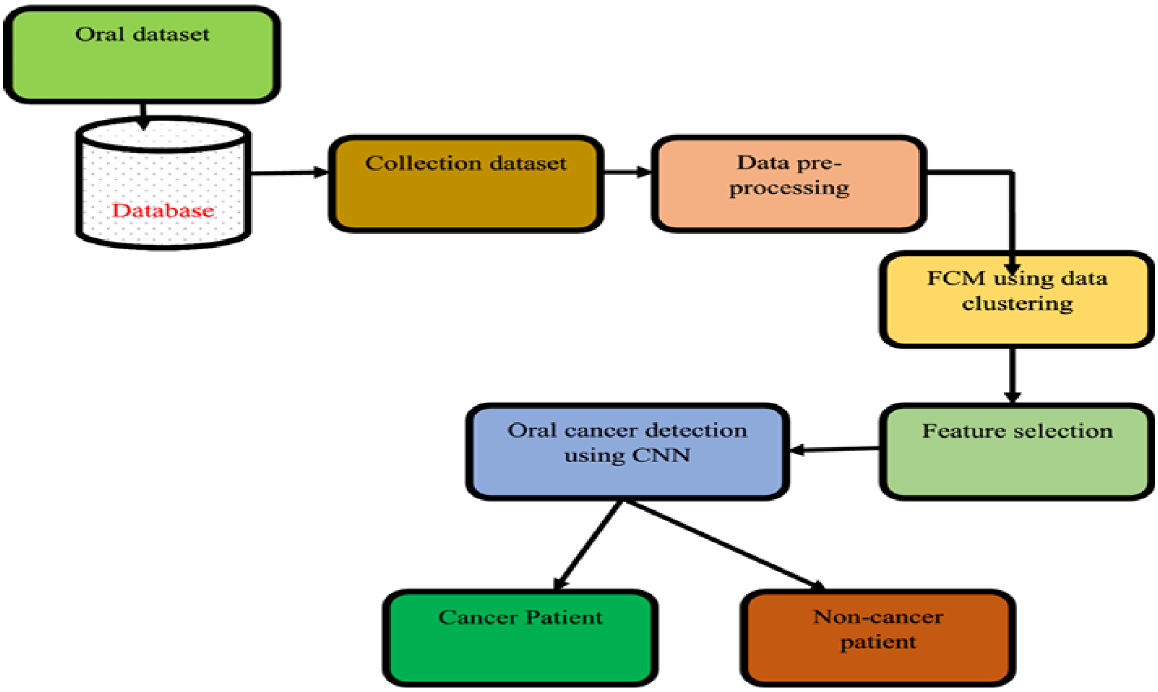

Fig 1. Workflow of the project

V. RESULT ANALYSIS

Result analysis is performed to evaluate the effectiveness and accuracy of the proposed Oral Cancer Detection System. The system integrates a deep learning-based image classification model and a machine learning-based clinical risk prediction model. The performance of both models was analyzed using standard evaluation metrics to assess reliability and suitability for preliminary oral cancer screening..[1] Image-Based CNN Model Results The image-based model was trained and validated using an oral cavity image dataset that was categorized into cancer and non-cancer classes. The

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 13, Issue 5, May 2026

DOI: 10.17148/IARJSET.2026.13545

trained CNN was flawless in discrimination power between the two classes. In this approach, the level of accuracy was very high. This demonstrated an indication that the oral images had a high chance of being detected. The precision and recall rates in this approach were good. This demonstrated an indication that the cancer images had a high chance of being detected with minimal false alarms. In all medical gadgets, it was important to consider the fact that the failure to detect a patient with cancer may be dangerous. From the Confusion Matrix analysis, there was an improvement in the rate of the false negative. This demonstrated an indication that the approach was effective in the identification of cancer images. The ROC curve graph was of good AUC value.[2] Clinical Data-Based Model Results The clinical prediction model was evaluated using a synthetic clinical dataset containing patient attributes such as age, tobacco usage, alcohol consumption, and presence of oral lesions. The model generated probability-based predictions indicating the likelihood of oral cancer. The clinical model effectively identified high-risk cases based on symptom patterns and lifestyle factors. While the clinical model alone does not provide definitive diagnosis, it served as a valuable complementary tool to the image-based model by highlighting potential risk levels. The probability outputs enabled better interpretability, allowing healthcare professionals to understand the level of risk rather than relying on a binary outcome alone. [3] Combined Model Analysis The integration of image-based and clinical data-based predictions significantly improved the overall reliability of the system. The combined approach ensured that both visual evidence and patient health parameters were considered during screening. Dept. of MCA, NIE, Mysuru 39 Oral cancer detection 2025-26 Dept. of MCA, NIE, Mysuru 40 In cases where the image-based model produced borderline confidence scores, the clinical risk assessment provided additional support for decision-making. This hybrid analysis reduced ambiguity and enhanced confidence in predictions. [4] Visualization of Results The system presents results through clear visual elements such as confidence scores, probability indicators, and classification labels within the Streamlit interface. Graphical representations like confusion matrices and ROC curves further support performance evaluation and interpretability.

Test case	Input	Expected Result	Status
T1	Valid oral cavity image	Error message displayed	pass
T2	Cancerous oral image	Cancer detected	pass
T3	Non-cancerous oral image	Non-cancer detected	pass
T4	Invalid file format	Error message displayed	pass

Table 1: Image-Based Testing

Test case	Input	Expected Result	Status
T4	Complete clinical details	Data accepted	pass
T5	Missing clinical fields	Validation error	pass
T6	High-risk symptoms	High risk probability	pass
T7	Low risk symptoms	Low risk probability	pass

Table 2: Clinical Data Testing

Test case	Input	Expected Result	Status
T8	Image+clinical data	Combined prediction show	pass
T9	Repeated prediction	Stable output	pass
T10	Submit without image	Warning displayed	pass
T11	Submit without data	Error displayed	pass

Table 3:System integrated testing

[5] Observations

[1] The CNN model demonstrated strong capability in detecting oral cancer from images. [2]The clinical model effectively supported risk assessment based on patient data. [3]Combined predictions improved diagnostic confidence and reduced misclassification risk.[4]The system performed efficiently in real-time scenarios.[5] The system successfully handled valid and invalid inputs without crashing.[6] Image pre-processing and prediction were performed efficiently.[7] Clinical data validation improved reliability of predictions.[8] Combined image and clinical analysis enhanced diagnostic confidence. [9] Streamlit interface provided smooth real-time interaction.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 5, May 2026

DOI: 10.17148/IARJSET.2026.13545

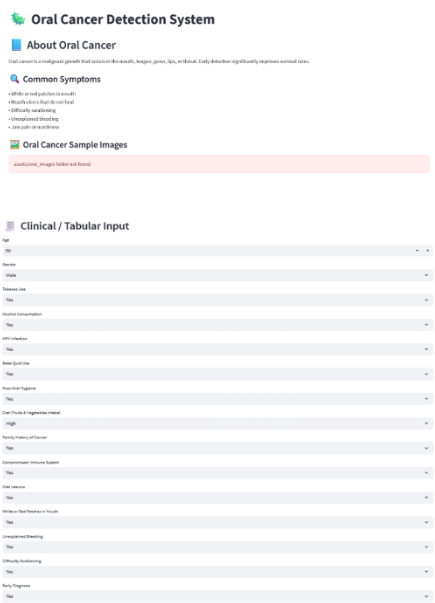

Fig 2. Manual detection age

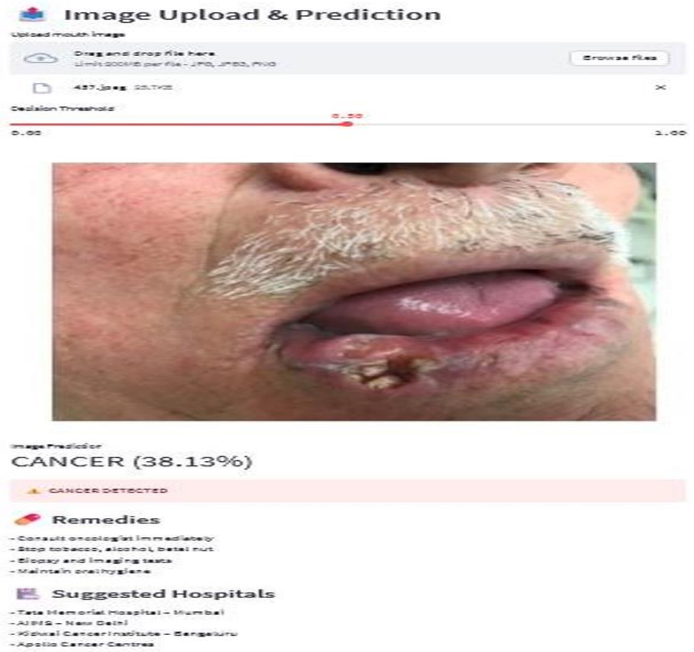

Fig 3. Image detection page

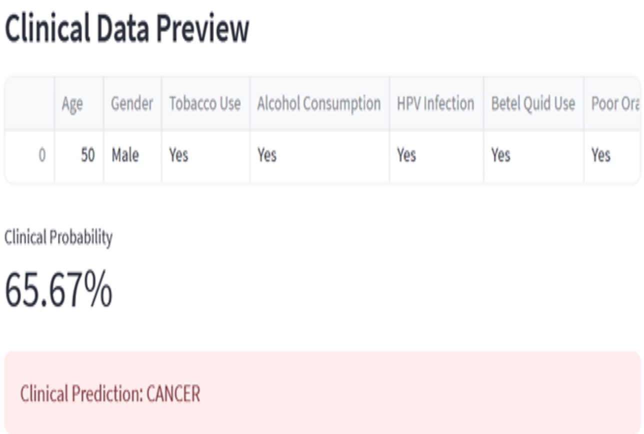

Fig 4. Manual detection result

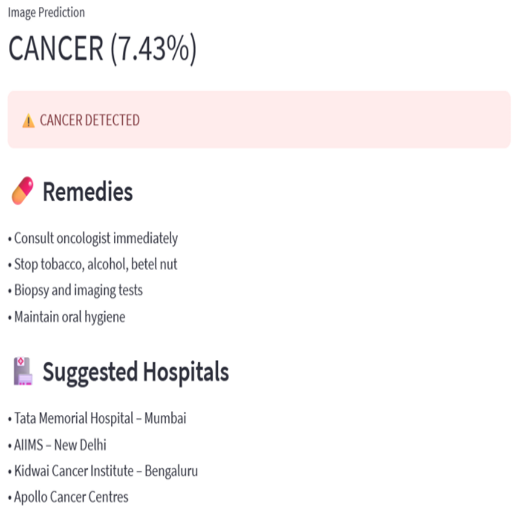

Fig 5. Image detection result

VI. CONCLUSION

This project successfully demonstrates the design and development of an intelligent Oral Cancer Detection System using machine learning and deep learning techniques. By combining a Convolutional Neural Network (CNN) for image-based analysis with a clinical data-based machine learning model, the system provides a comprehensive approach for early-stage oral cancer screening. The CNN model effectively extracts deep visual features from oral cavity images and accurately classifies them as cancerous or non-cancerous, while the clinical prediction model evaluates patient risk based on lifestyle habits and symptom-related attributes. The integration of image and clinical data enhances diagnostic reliability by reducing dependence on a single data source. The system's web-based deployment using Streamlit ensures real-time prediction, ease of accessibility, and user-friendly interaction, making it suitable for use by healthcare professionals, screening camps, and educational institutions. The modular system design, efficient implementation, and successful testing confirm that the system meets both functional and non-functional requirements. Overall, the proposed system serves as a valuable decision-support tool that can assist in early detection, reduce diagnostic delays, and contribute to improved oral cancer awareness and prevention.

DOI: 10.17148/IARJSET.2026.13545

VII. ACKNOWLEDGMENT

I extend my deepest gratitude to Mr.Sujayeendra Rao, project supervisor, for her expert guidance, constructive feedback, and steadfast support throughout this research. Sincere appreciation is due to the faculty and staff of the National Institute of Engineering, Mysuru, for facilitating critical resources and institutional infrastructure. Heartfelt thanks go to peers and classmates for their collaborative input and motivation, and to my parents for their unwavering emotional and moral encouragement. Finally, acknowledgment is given to all who contributed directly or indirectly to this project's successful completion.

REFERENCES

[1]. World Health Organization (WHO), Oral Cancer Fact Sheet, WHO Publications, Geneva, Switzerland, 2023.
[2]. American Cancer Society, Oral Cavity and Oropharyngeal Cancer Overview, ACS Journals, 2022.
[3]. LeCun, Y., Bengio, Y., & Hinton, G., "Deep Learning," Nature, vol. 521, no. 7553, pp. 436 444, 2015
[4]. Esteva, A., Kuprel, B., Novoa, R. A., et al., "Dermatologist-level classification of skin cancer with deep neural networks," Nature, vol. 542, pp. 115–118, 2017.
[5]. Pedregosa, F., Varoquaux, G., Gramfort, A., et al., "Scikit-learn: Machine Learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.
[6]. Chollet, F., Deep Learning with Python, Manning Publications, 2018.
[7]. Kaggle, Oral Cancer Image Dataset, Available: https://www.kaggle.com (accessed 2024).
[8]. TensorFlow Documentation, Deep Learning Framework, Available: https://www.tensorflow.org.
[9]. Keras Documentation, High-Level Neural Networks API, Available: https://keras.io.
[10]. Streamlit Documentation, Streamlit: The fastest way to build ML apps, Available: https://streamlit.io.

