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Detection of Oral Cancer in Smart Phone using Deep Learning for Early Diagnosis

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ABSTRACT

Oral cancer (OC) is a prevalent and complex disease with high severity, posing a major public health concern. Early diagnosis is critical for effective treatment and increased survival rates. In India, oral cancer ranks as the eighth most common cancer, contributing to approximately 130,000 deaths annually. The application of advanced technologies and deep learning algorithms holds significant promise for the early detection and classification of oral cancer. Early identification is essential for improving patient outcomes and saving lives. In recent years, deep learning (DL) has gained momentum as a powerful tool in the early diagnosis of various diseases, including oral cancer. The integration of artificial intelligence (AI) in cancer screening and detection demands a well-structured and strategic approach. This study presents an innovative method for detecting oral cancer using deep learning techniques. The system is built using Python as the main programming language, Flask as the backend framework, and HTML, CSS, and JavaScript for the frontend interface. Two state-of-the-art deep learning architectures, ResNet152V2 and MobileNet, are employed to classify oral images accurately. The ResNet152V2 model achieves impressive training accuracy of 98.00% and validation accuracy of 93.00%, while the MobileNet model achieves a training accuracy of 97.00% and validation accuracy of 92.00%. The findings highlight the efficacy of integrating multiple data modalities for more accurate early detection of potential malignancies compared to using only image data. The outcomes could pave the way for improved clinical decision-making and patient outcomes.

Keywords: *Artificial intelligence, Oral cancer, Convolutional neural networks (CNN), Binary and multi-class classification, Colour spaces, Early detection, Feature importance, White light images.*

1. INTRODUCTION

Oral cancer (OC) represents a major public health issue, where early detection is vital for successful treatment and increased survival rates. Cancer, in general, is characterized by the abnormal growth of cells that can invade and spread to other parts of the body. Oral cancer, classified under head and neck cancers, refers to malignant growths occurring in the tissues of the oral cavity or oropharynx. This includes cancer affecting the lips, tongue, cheeks, floor of the mouth, hard and soft palates, sinuses, and throat. Globally, oral cancer ranks sixth among all types of cancer. It is more commonly diagnosed in men than women and typically affects individuals over the age of 40. The occurrence of oral cancer varies across regions, with higher prevalence in areas where risk factors such as tobacco use and betel quid chewing are widespread-especially in South Asia. India bears the highest burden of oral cancer, accounting for nearly one-third of global cases. Compared to other countries, the situation is more critical in India, as approximately 70% of cases are detected at advanced stages (Stage III-IV, as classified by the American Joint Committee on Cancer). This delayed diagnosis severely reduces the chances of successful treatment, contributing to a high mortality rate. However, if detected early, the survival rate could be improved to nearly 90%. Hence, there is an urgent need for diagnostic methods that are user-friendly, quick, accurate, and non-invasive. In response to this need, we propose a novel approach that utilizes both colour and texture features extracted from various colour spaces to classify oral cancer at its pre-cancerous stages. Texture features play a critical role in image segmentation, classification, and synthesis. Although many techniques for texture feature extraction have been introduced over the years, the research landscape remains open to further exploration. Alongside texture, colour is another vital element in how humans perceive and process images. Despite its importance, colour texture analysis has received limited attention in research, with most existing studies relying on grayscale-based texture analysis methods.

In the field of artificial intelligence, Machine Learning (ML) and Deep Learning (DL) have emerged as transformative technologies, significantly advancing AI capabilities. Deep learning, in particular, allows machines to interpret and learn from complex data patterns, closely resembling the way the human brain processes information. This study introduces the core principles of deep learning, highlighting its key concepts, wide-ranging applications, and the profound impact it has made across various fields. Machine learning, a subset of AI, involves combining data with statistical techniques to predict outcomes, which can then inform meaningful decisions. It is closely linked with data mining and Bayesian predictive modeling. In this process, the system receives input data and applies algorithms to generate predictions or insights. The scope of ML and DL applications has grown rapidly in recent years, driven by technological advancements and the increased availability of digitized data. This includes electronic health records and medical images, particularly in the fields of pathology and radiology. ML and DL techniques have demonstrated significant success in classifying oral cancer lesions at different stages. A review of existing literature highlights a strong demand for non-invasive, real-time diagnostic methods for oral cancer. Such techniques should deliver reliable performance with minimal false positives, paving the way for more accurate and accessible cancer detection.

It has also been noted that individual colour spaces remain largely underexplored in existing research. Similarly, the use of coloured texture features, particularly in the context of white light imaging for oral cancer (OC) classification, has received limited attention. To address this gap, the present study proposes a method for classifying oral cancer into its pre-cancerous stages using white light images. The integration of the deep learning models with the Flask web framework allows for real-time processing and classification of oral images. This capability is crucial for timely diagnosis and intervention, potentially improving patient outcomes by enabling early detection of oral cancer. The objective is to minimize diagnostic bias among physicians and enable real-time lesion classification with minimal resource requirements.

2. THE SIGNIFICANCE OF THE STUDY

"Detection of Oral Cancer in Smartphones Using Deep Learning for Early Diagnosis" lies in its potential to revolutionize early cancer detection through AI-driven mobile technology. Oral cancer, if detected early, significantly improves treatment success and survival rates. This study integrates deep learning algorithms with smartphone applications to provide a cost-effective, accessible, and non-invasive diagnostic tool. It is particularly beneficial for individuals in remote areas with limited healthcare facilities. Additionally, this research contributes to the advancement of AI in medical diagnostics, enhances telemedicine capabilities, and promotes proactive healthcare solutions for better disease prevention and management.

3. LITERATURE SURVEY

Esra Yildiz et al., (2025) presented an effective smartphone-based imaging diagnosis method powered by a deep learning algorithm to address the challenges of automatic detection of oral cancer. The approach aims to facilitate early diagnosis, particularly in resource-limited settings, by leveraging the accessibility of smartphones and the capabilities of deep learning models. José J. M. et al., (2025), explored the application of diffusion models in classifying skin and oral cancers using medical images. The models demonstrated competitive performance compared to traditional deep learning approaches, suggesting their potential utility in smartphone-based diagnostic tools for early cancer detection. Hirthik Mathesh G.V et al., (2025) introduced a novel method combining Capsule Networks (CapsNet) and Deep Belief Networks for the detection and identification of oral leukoplakia, a potentially malignant disorder. The study emphasizes the importance of early detection and proposes an automated system that could be integrated into smartphone applications for widespread screening. Warin. K et al., (2024) aimed to develop an AI-based model that uses a portable electronic oral endoscope to capture intraoral images for the detection of oral cancer. Utilizing U-Net and ResNet-34 deep learning models, the system demonstrated high accuracy in identifying cancerous lesions. The research emphasizes the feasibility of deploying such technology in primary care settings to facilitate early diagnosis. G. A. I. Devindi et al., (2024) introduced a multimodal deep convolutional neural network (CNN) pipeline designed for the early detection of oral cavity abnormalities. The study emphasizes the integration of various data modalities to enhance diagnostic accuracy. The proposed system leverages advanced CNN architectures to process and analyze images captured via smartphones, facilitating early and accessible detection of oral cancer. Bibek Goswami et al., (2024) developed a classification framework employing the LightGBM algorithm to categorize oral cancer into pre-cancerous stages using white light images. The study focuses on enhancing early detection capabilities through machine learning techniques, aiming to improve diagnostic precision and facilitate timely intervention.

. Keser G et al. (2023) conducted a retrospective study employing a deep learning algorithm for the classification of oral lichen planus lesions from photographic images. The model achieved high diagnostic accuracy, indicating its potential as a non-invasive tool for early detection and monitoring of oral potentially malignant disorders. Warin K et al. (2023) examined the impact of handheld AI-based tools, focusing on Convolutional Neural Networks (CNNs) and their advanced architectures in oral cancer diagnosis. The study highlights the potential of deep learning in enhancing diagnostic accuracy and integrating telemedicine. Srisuwan T et al. (2023) explored the implementation of AI during the early stages of cancer for the proper detection and treatment of oral cancer. Performance evaluations of several deep learning and machine learning models have been carried out, showing that deep learning models can overcome challenges associated with early cancerous lesions in the mouth. Singh A et al. (2023) assessed the diagnostic performance of AI in detecting oral cancer, emphasizing its reliability in early detection through medical imaging. The findings supported the use of AI as a reliable approach for early detection, particularly in resource-limited settings. Sharma N et al. (2023) investigated various datasets and algorithms used in machine learning and deep learning for oral cancer diagnosis. It emphasized the importance of modality selection in model performance, discussing the challenges and opportunities in early detection. Koriakina N et al. (2022) explored comparison of deep multiple instance learning (MIL) and conventional deep single instance learning (SIL) for oral cancer detection using cytological images. Results indicated that SIL outperformed MIL in accuracy, suggesting that per-instance labeling provides more reliable diagnostic performance. The research contributes to optimizing AI models for cytology-based cancer detection. Chen L et al. (2022) discussed the transformative role of AI in oral cancer diagnosis and treatment. It emphasized early detection, risk modeling, and addressing data heterogeneity, underscoring the need for uniform standards and long-term investigations. Ahmed S et al. (2022) explored the integration of AI in oral cancer diagnosis, focusing on early detection, risk modeling, and prognosis using histopathology images. It discussed the challenges of data heterogeneity and the need for standardized protocols. Ferrer-Sánchez A et al. (2022) developed a deep learning model to predict the risk of cancer and the grade of dysplasia in leukoplakia lesions. Their study utilized clinical images to train the model, which showed promising results in risk stratification. This approach could aid clinicians in decision-making processes regarding biopsy and treatment planning.

Lin et al. (2021) developed a smartphone-based imaging method utilizing deep learning algorithms for the automatic detection of oral cancer. Their study demonstrated the potential of combining mobile imaging with AI to facilitate early diagnosis, especially in resource-limited settings. The approach aimed to provide a cost-effective and accessible tool for primary screening of oral malignancies. Warin et al. (2021) focused on the automatic classification and detection of oral cancer in photographic images using deep learning algorithms. The researchers employed convolutional neural networks to analyze images captured via smartphones, achieving high accuracy in distinguishing malignant lesions. Their work highlights the feasibility of deploying AI-driven diagnostic tools in telemedicine applications. Tanriver et al. (2021) explored the automated detection and classification of oral lesions using deep learning to identify oral potentially malignant disorders. Their research demonstrated the effectiveness of AI models in analyzing clinical images for early signs of malignancy, suggesting a valuable role for deep learning in routine oral examinations. Wang X & Li BB (2021) discussed the application of deep learning in the multiomics diagnosis and analysis of head and neck tumors, including oral cancer. They emphasized the integration of various data types, such as imaging and genomic information, to enhance diagnostic accuracy and personalized treatment planning through AI technologies. Frontiers in Oral Health (2021) provided an overview of deep learning applications in oral squamous cell carcinoma (OSCC), covering aspects from precise diagnosis to treatment planning. It highlighted how automated image analysis and AI algorithms can assist clinicians in making informed decisions, ultimately contributing to improved patient outcomes in oral cancer care. Morikawa T et al. (2020) explored the application of image processing techniques in diagnosing oral cancer and potentially malignant disorders. The study emphasized the role of optical instruments in enhancing diagnostic accuracy. By analyzing various imaging modalities, the research highlighted the potential of integrating advanced image analysis for early detection of oral malignancies. This work underscores the importance of technological advancements in improving oral cancer diagnostics. Sukegawa S et al. (2020) assessed the efficacy of oral cytology as a primary screening tool for oral cancer and precancerous lesions. The research demonstrated that non-invasive cytological methods could effectively identify malignant transformations in the oral cavity. The findings support the integration of cytology-based screening in routine dental check-ups, potentially facilitating early intervention and improving patient outcomes. Sunny S et al. (2020) developed a smart tele-cytology platform aimed at point-of-care screening for oral cancer. The system leverages digital imaging and remote analysis to provide rapid assessments of oral lesions. Their approach demonstrated high accuracy in detecting malignant cells, suggesting its utility in resource-limited settings. This innovation represents a significant step toward accessible and efficient oral cancer screening. Ye X et al. (2020) conducted a meta-analysis comparing two computer-assisted screening methods for diagnosing oral precancer and cancer. The study evaluated the diagnostic accuracy, sensitivity, and specificity of these technologies. Results indicated that computer-assisted methods could enhance early detection rates, offering a valuable supplement to traditional diagnostic procedures. This work highlights the growing role of technology in oral oncology. Liu Y et al. (2020) focused on the quantitative prediction of oral cancer risk in patients with oral leukoplakia. Utilizing advanced analytical techniques, the study aimed to stratify patients based on their risk profiles. The research findings contribute to personalized medicine approaches, enabling targeted monitoring and early intervention strategies for high-risk individuals.

Jeyaraj & Samuel Nadar (2019) conducted a comprehensive review of machine learning algorithms in the early detection of oral cancer. They analyzed various studies employing techniques like support vector machines, decision trees, and neural networks. The review emphasized the growing role of AI in enhancing diagnostic accuracy and reducing subjectivity. It also discussed the potential of integrating these algorithms into portable devices, highlighting the feasibility of smartphone-based screening tools for oral cancer. Das et al. (2019) developed a smartphone-based imaging system combined with machine learning algorithms to detect oral potentially malignant disorders (OPMDs). Their study involved capturing images of oral lesions using a smartphone and analyzing them with a trained classifier. The system demonstrated promising accuracy in differentiating between benign and potentially malignant lesions. This research underscored the potential of leveraging ubiquitous smartphone technology for accessible and cost-effective oral cancer screening, especially in low-resource settings. Ariji et al. (2018) explored the application of deep learning in dental radiology, focusing on the detection of mandibular condyle osteoarthritis. Their study utilized CNNs to analyze panoramic radiographs, achieving high diagnostic accuracy. While not directly targeting oral cancer, this research highlighted the efficacy of deep learning in oral and maxillofacial imaging. The methodologies developed have been instrumental in advancing AI-driven diagnostic tools for various oral pathologies, including malignancies. Poedjiastoeti et al. (2018) developed a deep learning model to detect oral squamous cell carcinoma (OSCC) from histopathological images. The CNN-based system achieved high sensitivity and specificity, demonstrating its potential as a diagnostic aid. By automating the analysis of biopsy images, the model aimed to assist pathologists in identifying malignant lesions more efficiently. This research marked a significant step toward integrating AI into oral cancer diagnostics, paving the way for future smartphone-based applications. **Prakash et al. (2013)** developed OScan, a low-cost, smartphone-based device designed to detect oral cancer. This innovative tool attaches to a smartphone or digital camera, enabling health workers to capture images of patients' mouths and transmit them to offsite experts for analysis. The primary goal was to facilitate early detection of oral cancer in regions with limited access to dental care, such as rural India, where the dentist-to-population ratio can be as high as 1:250,000. By leveraging the widespread availability of smartphones and digital imaging, OScan aimed to provide an accessible and cost-effective screening solution. This approach not only addressed the scarcity of specialized healthcare providers but also sought to reduce the high incidence and mortality rates associated with late-stage oral cancer diagnoses in underserved areas. The development of OScan marked a significant step toward integrating mobile technology into public health initiatives for cancer detection.

These studies collectively highlight the advancements in integrating deep learning algorithms with smartphone technology to facilitate early detection of oral cancer. The implementation of such systems holds promise for improving diagnostic accessibility and outcomes, particularly in regions with limited healthcare resources. Therefore, in this paper, we aim to develop a technique for the classification of OC into its pre-cancerous stages using effective smartphone-based imaging diagnosis method powered by a deep learning algorithm to address the challenges of automatic detection of oral cancer. The approach aims to facilitate early diagnosis, particularly in resource-limited settings, by leveraging the accessibility of smartphones and the capabilities of deep learning models

4. DATASET

- **Created Class Directories:** Created separate directories for each class in our dataset named as “Cancer” and “Non cancer”.
- **Move Images to Class Directories:** Place each image in the directory corresponding to its class label. For instance, if an image is labeled as “Cancer”, we would move it to the “Cancer” directory. Similarly, if an image is labeled as “Non cancer”, we would move it to the “Non cancer” directory.
- By organizing the dataset in this structure, it becomes straightforward to load the data into our deep learning framework. This is because we can easily specify the directory path for each class when loading the data, ensuring that the correct images are loaded for each class and total dataset size is 750.

5. METHODOLOGY

The proposed method in this article comprises of first preprocessing the input image by converting the images into resizing images to a standard size, normalizing pixel values, and encoding labels if necessary. To achieve this, the Image Data Generator from Keras can be utilized. Finally, a classifier was trained and tested on the selected features. The overall flow of this study is shown in Figure 1.

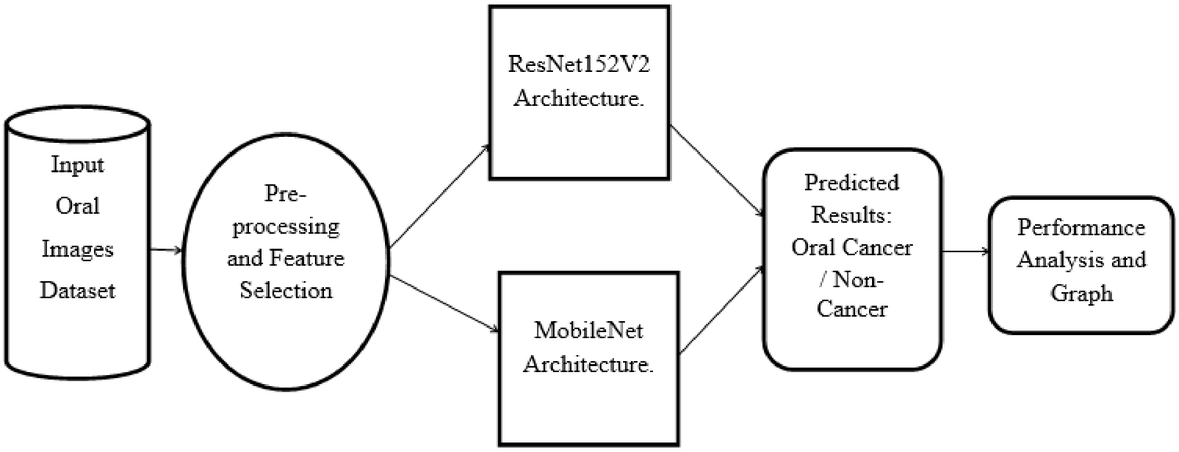

Figure 1. Flow diagram of the proposed methodology.

The figure 1. Shows the training procedure. The sample database contains all training oral finally cancer images. The classifier model is trained by using the extracted features and saved for use in the future.

A. INPUT DESIGN

The input design is the link between the information system and the user. It comprises the developing specification and procedures for data preparation and those steps are necessary to put transaction data in to a usable form for processing can be achieved by inspecting the computer to read data from a written or printed document or it can occur by having people keying the data directly into the system. The design of input focuses on controlling the amount of input required, controlling the errors, avoiding delay, avoiding extra steps and keeping the process simple. The input is designed in such a way so that it provides security and ease of use with retaining the privacy.

Input Design considered the following things:

- What data should be given as input?
- How the data should be arranged or coded?
- The dialog to guide the operating personnel in providing input.
- Methods for preparing input validations and steps to follow when error occur.

The output form of an information system should accomplish one or more of the following objectives.

1. Input Design is the process of converting a user-oriented description of the input into a computer-based system. This design is important to avoid errors in the data input process and show the correct direction to the management for getting correct information from the computerized system.
2. It is achieved by creating user-friendly screens for the data entry to handle large volume of data. The goal of designing input is to make data entry easier and to be free from errors. The data entry screen is designed in such a way that all the data manipulates can be performed. It also provides record viewing facilities.
3. When the data is entered it will check for its validity. Data can be entered with the help of screens. Appropriate messages are provided as when needed so that the user will not be in maize of instant. Thus the objective of input design is to create an input layout that is easy to follow.

a. Input Design for Oral Cancer Detection using Deep Learning:

The input design for the “Detection of Oral Cancer in Smartphones Using Deep Learning for Early Diagnosis” study focuses on how data is collected, formatted, and provided to the system for processing. It ensures that the inputs are accurately captured, correctly formatted, and efficiently used by the deep learning models.

b. Input Design:

- **Image Upload Interface:**
- **Functionality:** Users can upload oral images via the web interface.
- **Format:** Images should be in standard formats such as JPEG.
- **Validation:** Ensure the uploaded file is an image and meets size and resolution requirements.

- **Image Pre-processing:**
- **Normalization:** Scale pixel values to a range suitable for the deep learning models (e.g., 0-1).
- **Resizing:** Resize images to match the input size expected by the models (e.g., 224x224 pixels for MobileNet).
- **Augmentation:** Apply techniques like rotation, flipping, and zooming to enhance model robustness during training.
- **Metadata Collection:**
- **Patient Information:** Collect optional metadata like age, gender, and medical history for comprehensive analysis.
- **Image Labeling:** Ensure images are labeled as cancerous or non-cancerous, either manually or via existing datasets.
- **Data Storage:**
- **Database:** Store uploaded images and associated metadata in a secure database.
- **Directory Structure:** Organize images in a structured directory format for easy access during model training and inference.

c. Input Design Process:

- **User Interface (UI):**
- A simple, intuitive web form for image upload.
- Input fields for optional metadata collection.
- Validation messages and guidelines to ensure correct input.
- **Backend Processing:**
- Use Flask to handle image uploads and preprocessing.
- Implement image validation and preprocessing scripts.
- Store processed images and metadata in a database or file system.

d. Example Input Flow:

- User accesses the web application and uploads an image of the oral cavity.
- The system validates the image format and size.
- Pre-processing is applied to resize and normalize the image.
- The image and metadata are stored in the backend database for further processing by the deep learning model.

B. OUTPUT DESIGN

A quality output is one, which meets the requirements of the end user and presents the information clearly. In any system results of processing are communicated to the users and to other system through outputs. In output design it is determined how the information is to be displaced for immediate need and also the hard copy output. It is the most important and direct source information to the user. Efficient and intelligent output design improves the system's relationship to help user decision-making.

1. Designing computer output should proceed in an organized, well thought out manner; the right output must be developed while ensuring that each output element is designed so that people will find the system can use easily and effectively. When analysis design computer output, they should Identify the specific output that is needed to meet the requirements.
2. Select methods for presenting information.
3. Create document, report, or other formats that contain information produced by the system.

The output form of an information system should accomplish one or more of the following objectives.

- Convey information about past activities, current status or projections of the
- Future.
- Signal important events, opportunities, problems, or warnings.
- Trigger an action.
- Confirm an action.

a. Output Design:

The output design focuses on how the results from the deep learning models are presented to the users. It ensures that the outputs are clear, accurate, and actionable.

b. Output Design:

- **Classification Results:**
- ❖ **Cancer Detection:** The primary output is whether the uploaded image is classified as cancerous or non-cancerous.
- **User Interface (UI):**
- ❖ **Results Page:** A dedicated page to display the results of the image analysis.

c. Output Design Process:

- **Result Presentation:**
  - Design a results page that clearly displays the classification result.

d. Example Output Flow:

- ❖ After processing the uploaded image, the system classifies it as either cancerous or non-cancerous.
- ❖ The results page displays the classification result along performance analaysis.
- ❖ By designing clear and efficient input and output processes, the system ensures accurate data collection and meaningful presentation of results, enhancing the overall user experience and supporting effective oral cancer detection and diagnosis.

C. ACTIVITY DIAGRAM

Activity diagrams (Figure 2) are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.

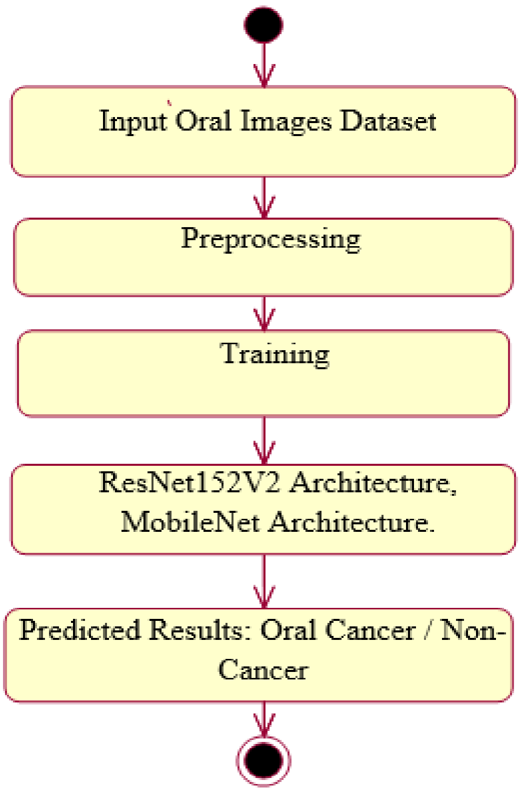

Figure 2. Flow diagram of the graphical representations of workflows.

This study leverages a dataset comprising annotated images of oral cavities acquired through mobile phone cameras under the natural light or the light source of the dental chair. A total of 938 images were used. Each of the 938 images includes annotations for the oral cavity boundary and five associated metadata values: age, sex, smoking, alcohol usage, and betel quid chewing.

Figure 3. & Figure 4. shows a set of sample images belonging with features captured from different anatomic sites of the oral cavity, including the tongue, palate, labial mucosa (upper or lower), buccal mucosa (left or right), and the floor of the mouth. Subsequently, the images were partitioned into training, validation, and testing sets using a ratio of 0.6, 0.2, and 0.2, respectively. The validation set was specifically set aside to adjust hyper parameters and track the model's ability to generalize during the training process. To prevent data leakage due to the presence of multiple images per patient, the dataset was divided so that all images belonging to the same patient were kept together within a single split.

Figure 3. Sample images in the cancerous stage

Figure 4. Sample images in the Non-cancerous stage

Table 1. Number and percentage of images in each category.

Class	Non-cancerous	Cancerous	Total
Train	188	375	563
Validation	62	125	187
Test	62	126	188
Percentage per category (%)	33	67	

Source: Primary data

Table 1. Shows a breakdown of the number of images used in each category. The distribution of classes in all splits was preserved to mirror the same proportions as in the overall dataset. From the above analysis, it was evident that advanced deep learning models with a well-curated dataset and an intuitive user interface, establishing a comprehensive framework for improving the detection and diagnosis of oral cancer. Two deep learning architectures ResNet152V2 and MobileNet performs the best for the dataset and hence, it was considered the optimal classifier for this work.

6. RESULTS AND DISCUSSION

- This study for oral cancer detection employs advanced deep learning techniques to enhance the accuracy and efficiency of diagnostic processes. This system is developed using Python as the primary coding language, with Flask serving as the web framework and HTML, CSS, and JavaScript providing a user-friendly frontend interface.
- Two deep learning architectures are at the core of this system: ResNet152V2 and MobileNet. Both models are trained on a dataset comprising 500 oral cancer images and 250 non-cancer oral images, each meticulously labeled to facilitate accurate classification.
- The ResNet152V2 architecture, known for its deep residual networks, is utilized to achieve high accuracy in detecting oral cancer. This model has been trained to reach a training accuracy of 98.00% and a validation accuracy of 93.00%, indicating its robustness in handling the complexities of medical image classification.
- Similarly, the MobileNet architecture, optimized for efficient computation, is employed to balance performance with resource utilization. This model achieves a training accuracy of 97.00% and a validation accuracy of 92.00%, making it suitable for deployment in environments with limited computational resources.
- The dataset used in this study is a balanced collection of 500 cancerous and 250 non-cancerous oral images. Each image has been carefully labeled to ensure precise classification, facilitating the development of reliable models for oral cancer detection. This dataset serves as a foundational resource for training and evaluating the deep learning models.
- The frontend interface, developed using HTML, CSS, and JavaScript, provides an intuitive platform for users to interact with the system. This interface allows healthcare professionals to upload oral images for real-time classification, supporting timely and accurate diagnostic decisions.
- Overall, this system integrates advanced deep learning models with a well-curated dataset and an intuitive user interface, establishing a comprehensive framework for improving the detection and diagnosis of oral cancer.

7. ADVANTAGES OF THIS SYSTEM

- **High Accuracy and Robustness:** This system leverages advanced deep learning architectures, ResNet152V2 and MobileNet, which have demonstrated high training and validation accuracies (98.00% and 93.00% for ResNet152V2, 97.00% and 92.00% for MobileNet). This ensures reliable and precise detection of oral cancer, reducing the likelihood of false negatives and false positives.
- **Automated Feature Extraction:** Unlike traditional machine learning methods, the deep learning models used in this system can automatically extract relevant features from the images. This eliminates the need for extensive manual feature engineering, simplifying the workflow and ensuring that subtle patterns crucial for diagnosis are not overlooked.
- **Scalability and Efficiency:** The MobileNet architecture is specifically designed for efficiency, making the system suitable for deployment in environments with limited computational resources, such as mobile devices or small clinics. This scalability ensures broader accessibility and practical use in diverse healthcare settings.
- **User-Friendly Interface:** The frontend interface developed using HTML, CSS, and JavaScript is intuitive and easy to use. Healthcare professionals can seamlessly interact with the system, uploading images and receiving real-time classifications, which facilitate quick and informed decision-making in clinical practice.
- **Real-Time Detection:** The integration of the deep learning models with the Flask web framework allows for real-time processing and classification of oral images. This capability is crucial for timely diagnosis and intervention, potentially improving patient outcomes by enabling early detection of oral cancer.
- **Balanced and Well-Curated Dataset:** The dataset comprises 500 oral cancer images and 250 non-cancer oral images, meticulously labeled to ensure accurate training and validation of the models. The balanced nature of the dataset helps in mitigating biases, leading to more generalizable and reliable model performance.
- **Enhanced Diagnostic Support:** By providing an automated and highly accurate diagnostic tool, the proposed system supports healthcare professionals in making more accurate and consistent diagnoses. This can be particularly beneficial in settings with limited access to specialized oncologists, helping bridge the gap in medical expertise.

- **Integration Potential:** The system's architecture, built using Flask, allows for easy integration with existing healthcare management systems and electronic health records (EHRs). This interoperability enhances the overall utility of the system, making it a valuable addition to comprehensive healthcare solutions.
- **Continuous Learning and Improvement:** The deep learning models can be continuously trained with new data, allowing the system to evolve and improve over time. As more labeled images become available, the models can be fine-tuned to maintain high performance and adapt to new patterns or variations in the data.
- Overall, this system offers significant advancements in the detection and diagnosis of oral cancer, combining the strengths of deep learning with practical usability to support better healthcare outcomes.

8. ECONOMIC FEASIBILITY OF THE STUDY

This study is carried out to check the economic impact that the system will have on the organization. The amount of fund that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased.

Economic feasibility is a pivotal aspect of the overall feasibility study process that focuses specifically on assessing the financial viability of a project. It involves a comprehensive analysis of the project's costs and potential benefits to determine whether the investment is economically justifiable. This assessment is crucial for making informed decisions about whether to proceed with a project, as it directly impacts an organization's financial health and long-term sustainability.

Importance of Economic Feasibility:

Economic feasibility addresses the fundamental question: Is the project financially worthwhile? This aspect of the feasibility study delves into the financial implications of the project and provides decision-makers with insights into the potential returns, risks, and overall financial impact. It helps organizations allocate resources wisely, avoid wastage, and ensure that projects align with their financial goals and constraints.

Economic feasibility is a critical checkpoint in the feasibility study process. It empowers organizations to assess the financial viability of a project, make informed investment decisions, and allocate resources efficiently. By estimating costs, analyzing potential benefits, calculating financial metrics, and considering risks, organizations can determine whether a project aligns with their financial objectives and contributes positively to their bottom line. An in-depth analysis of economic feasibility ensures that projects are pursued with a clear understanding of their financial implications and a higher likelihood of achieving desired financial outcomes.

9. CONCLUSION

The study presents a generalized method for classifying oral cavity lesions into benign or malignant for binary classification and their pre-cancerous stages for multi-class classification. In this study, a novel technique of exploring the potential of advanced deep learning techniques in enhancing the accuracy and efficiency of oral cancer diagnosis. By utilizing the ResNet152V2 and MobileNet architectures, the system achieves high training and validation accuracies, indicating its robustness in handling complex medical image classification tasks. The balanced and meticulously labeled dataset ensures reliable model training, contributing to the overall effectiveness of the detection system. The integration of the system with a user-friendly frontend interface, developed using HTML, CSS, and JavaScript, facilitates easy interaction for healthcare professionals, enabling real-time image classification and timely diagnostic decisions. The use of Flask as the web framework supports seamless deployment and integration with existing healthcare systems, enhancing the practical applicability of the system in various clinical settings.

Overall, this study underscores the significant advancements that deep learning can bring to the field of medical diagnostics, particularly in the early detection of oral cancer. By providing a highly accurate, efficient, and user-friendly diagnostic tool, the system has the potential to significantly improve patient outcomes and support healthcare professionals in delivering better care. The successful implementation of this study highlights the importance and feasibility of adopting deep learning technologies in medical applications, paving the way for more innovative solutions in healthcare.

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