Recognition of Oral Cancer Progression Stages using White Light Imaging

[1] Divya S, [2] D Vikram Kumar, [3] Ch Yashwanth, [4] Dr N Srihari Rao
[1], [2], [3] UG Scholars, [4] Associate Professor, Department of computer science and Engineering,
Guru Nanak Institutions Technical Campus, Hyderabad, Telangana, India
*Corresponding author E-mail: divyasuniganti777@gmail.com

ABSTRACT:
Oral cancer is the sixth most frequent type of cancer worldwide, and it is one of the main causes of mortality. Although early detection during precancerous phases can greatly increase survival rates, late-stage diagnoses are the cause of its high mortality rate. Using image
analysis of oral lesions, this study suggests an effective diagnosis technique. The lightweight MobileNetV2 CNN architecture is used to classify the texture and color properties that are extracted from photos by exploring five color spaces. This model enhances accuracy while
still being appropriate for resource-constrained, mobile applications by fusing deep learning with handmade features. The approach performs well in binary and multi-class classification tasks, differentiating between benign, malignant, and precancerous lesions. Particularly in
underprivileged areas, its scalability and affordable design make it perfect for early oral cancer screening.
Keywords: Oral Cancer Detection, Pre-Cancerous Lesions, MobileNetV2, Convolutional Neural Network (CNN), Color and Texture Features, Medical Image Classification, Deep Learning, Lightweight Architecture, Real-Time Diagnosis, Resource-Constrained Devices

I. INTRODUCTION:

As the sixth most prevalent cancer and a major cause of cancer-related deaths, oral cancer is a major worldwide health concern. It contributed to around 10 million cancer- related deaths in 2020. The primary cause of the high death rate is late-stage diagnosis, when treatment is less successful. Effective treatments and mortality reduction depend on the early identification and categorization of precancerous lesions. However, conventional diagnostic techniques can be inconsistent, time-consuming, and require specific knowledge. Because of this, there is a pressing demand for automated solutions that can help healthcare providers detect and categorize oral lesions more precisely and early, allowing for prompt treatment and better patient outcomes.

A revolutionary machine learning-based method that distinguishes between benign, malignant, and precancerous oral cavity lesions is put forth in order to overcome this difficulty. MobileNetV2, a lightweight Convolutional Neural Network (CNN) designed for resource-constrained and mobile contexts, is the foundation of this system. By processing oral lesion images, this model eliminates the requirement for manual feature engineering by automatically extracting features. With its computationally efficient design, MobileNetV2 provides high classification accuracy and supports real-time processing. It is perfect for use in clinical settings with limited resources and mobile applications where sophisticated diagnostic infrastructure might not be accessible because of these features.

In order to detect lesion phases, the system analyzes oral lesion images over five distinct color spaces and extracts texture and color information. The lesion is classified as benign, malignant, or precancerous using the MobileNetV2 model using these features. Comprehensive analysis is ensured by the use of various color spaces, and the CNN architecture catches complex visual patterns that are essential for precise classification. Consequently, the system provides a diagnostic tool that is both scalable and easily accessible, hence facilitating the early diagnosis of oral cancer. Its effectiveness and mobility make it appropriate for extensive real-world application, particularly in underprivileged areas devoid of specialized medical knowledge or equipment.

II. LITERATURE SURVEY:

Title: Algorithm mediated early detection of oral cancer from image analysis

Author: Prachi Shah, Nilanjan Roy, Pinakin Dhandhukia

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This study introduces an automated method for early oral cancer detection by identifying premalignant lesions in buccal cavity images. Aimed at reducing cancer- related deaths in developing countries, the approach processes 20 images each of normal, Erythroplakia and Leukoplakia cases using MATLAB. Initially, images are classified as normal or abnormal using the maximum red pixel value. Based on the mean red value, images are further processed through either the Y or Cr channel in the YCbCr color space. For final classification, texture features are extracted using the Gray-Level Co-occurrence Matrix (GLCM), with entropy as the key metric. The system achieved 100% accuracy in the first step and 89% efficiency overall. A user-friendly graphical interface was also developed to present the diagnostic results effectively.

III. EXISTING SYSTEM:

LightGBM (Light Gradient Boosting Machine), a potent machine learning algorithm based on decision trees, is used in the current method for the identification of oral cancer. Because LightGBM performs well and efficiently when working with huge datasets, it is frequently utilized for classification tasks. In the current approach, a number of features are processed and input into the LightGBM model for classification, including color and texture information that is collected from photographs of the mouth cavity. LightGBM depends mostly on hand-crafted features and necessitates thorough hyperparameter tuning for best performance, despite its benefits, which include high speed, accuracy, and scalability for big datasets. Furthermore, LightGBM could not work well with image data that has complicated patterns, since it doesn't automatically capture hierarchical features or spatial links in the pictures. Additionally, the current system relies on a more conventional method of feature extraction and classification, which, although successful, might not be as flexible or efficient for real-time applications, particularly in settings with limited resources or mobility.

IV. PROPOSED SYSTEM:

A state-of-the-art Convolutional Neural Network (CNN) architecture created for efficiency in mobile and embedded devices, MobileNetV2 is introduced in the suggested system. MobileNetV2 provides a more sophisticated and resource-efficient method for detecting oral cancer than the conventional LightGBM algorithm. Compared to normal CNNs, MobileNetV2 is a lightweight CNN that uses depthwise separable convolutions, which drastically cut down on both computational cost and parameter count, making it perfect for real-time applications and mobile devices. The MobileNetV2 model in the suggested system automatically learns hierarchical feature representations from the raw image data after receiving photos of the mouth cavity. capturing texture and color features without requiring feature extraction that is done by hand. This increases the classification accuracy for benign, malignant, and precancerous lesions by helping the model identify intricate patterns in the images. The proposed MobileNetV2- based system is perfect for real-time, on- site diagnostics for oral cancer detection because it has several advantages over the current LightGBM-based system, such as faster processing times, increased accuracy, and flexibility for deployment in low-resource environments.

V. METHODOLOGIES:

Gathering the Dataset

Collecting the Dataset Building any machine learning model begins with data collection. Finding pertinent datasets that offer the data required for analysis and model training is part of it. This step involves gathering data from a variety of sources, such as public repositories, medical records, surveys, sensors, and other pertinent platforms. For the model to be accurate, the dataset must be representative of the issue domain, extensive, and diverse. The eventual performance and dependability of the machine learning system are directly impacted by the caliber and diversity of the data**.**

Data Examination

Examining and evaluating the gathered data to determine its structure, trends, and any underlying relationships is known as data examination. In this step, researchers and data scientists can thoroughly examine the dataset to find any possible problems that could impair model performance, like missing values, outliers, or inconsistencies. Descriptive statistics and visualizations are frequently employed in data analysis to highlight important features and offer insights into the information. This stage is crucial for directing later choices on preprocessing and model selection.

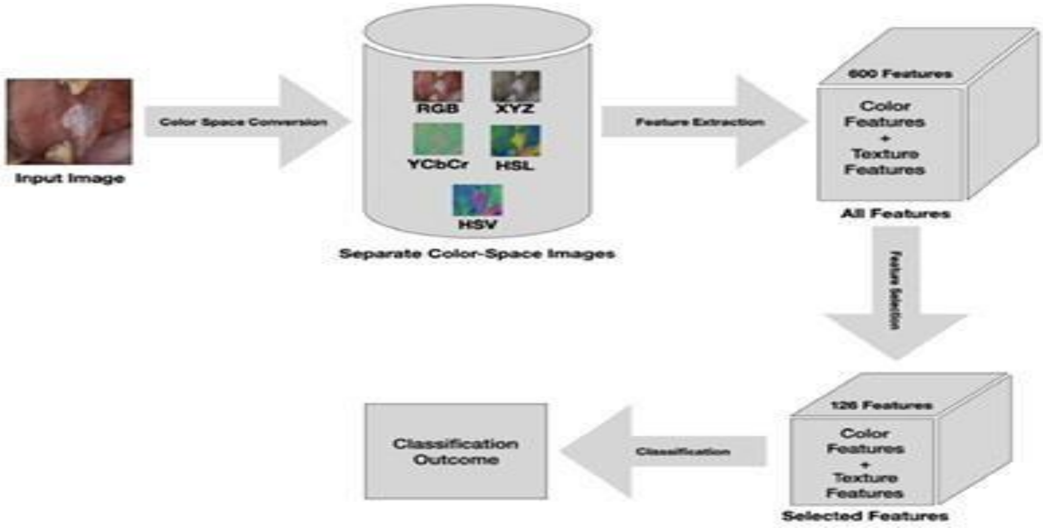
Data Cleaning

An essential step in getting the dataset ready for model training is data cleansing. In this step, errors are fixed, missing data is handled, and noisy or irrelevant information that can distort the analysis is eliminated. It also entails encoding category variables, normalizing or scaling numerical features, and making sure the dataset is uniform and consistent. Data cleaning enhances the quality of the input data, which has a direct effect on the model's performance, and guarantees that the dataset is prepared for the following stages of the machine learning pipeline.

Model Deployment

Model deployment is the process of placing a trained machine learning model into a live environment so it can be used with actual data. This step includes incorporating the model into an application, system, or service that benefits from its predictive capabilities. Deployment can occur across multiple platforms, including cloud infrastructure, mobile devices, or embedded hardware. Ensuring the model runs efficiently, scales well, and delivers predictions promptly is crucial for maintaining its accuracy and reliability in real-time scenarios.

VI. SYSTEM ARCHITECTURE:



VII. RESULT AND IMPLEMENTATION:

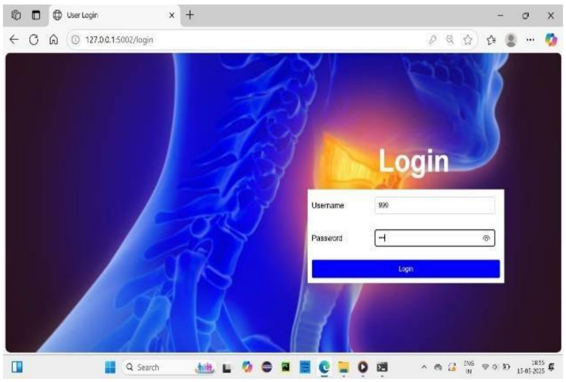


Fig 1: User Interface

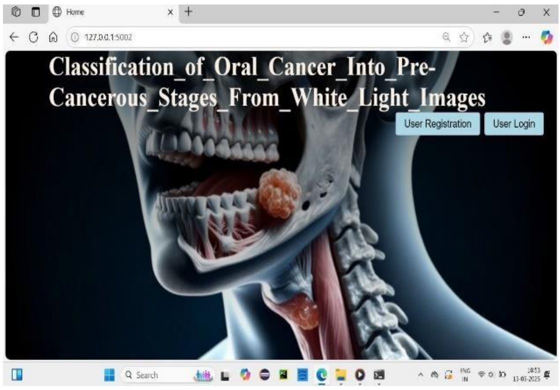


Fig 2: User Login

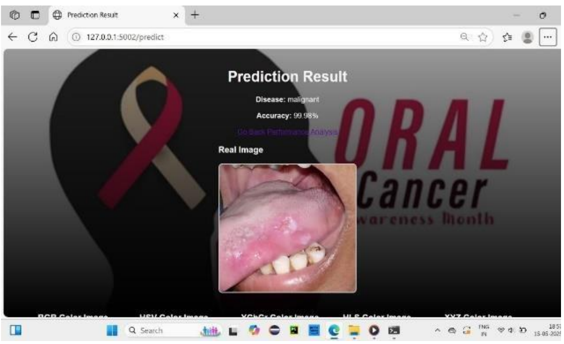


Fig 3: Result

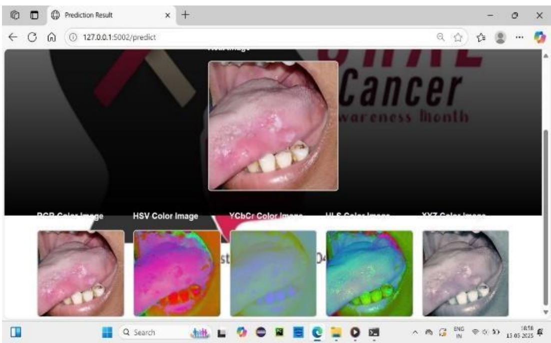


Fig 4: Result

VIII. FUTURE SCOPE:

While the current system demonstrates promising performance, there are several potential future enhancements to further improve its accuracy and usability. One enhancement could be the integration of advanced techniques like transfer learning to fine-tune the model on smaller, domain- specific datasets, thus improving its ability to handle rare cases. Another area of improvement is the expansion of the dataset to include more diverse images, representing various stages of oral lesions and different demographic groups. This would help the system generalize better across different populations. Additionally, incorporating real-time video analysis could be a valuable enhancement, allowing the system to detect lesions in dynamic conditions during medical examinations. Another potential enhancement involves implementing explainable AI techniques, which would allow medical professionals to understand the rationale behind the model's predictions, improving trust and adoption. Finally, optimizing the model for even faster processing on mobile devices and in low-resource settings could make the tool more accessible globally, especially in underdeveloped regions with limited access to advanced healthcare infrastructure.

IX. CONCLUSION:

In summary, this work offers a novel method for the early identification and categorization of lesions in the oral cavity by utilizing the MobileNetV2 architecture, which offers a portable and effective method for real-time analysis on mobile devices. By automating the classification of oral lesions into benign, malignant, and pre- cancerous stages, the system can significantly help medical professionals identify patients more quickly and accurately, which would ultimately lower the death rates from oral cancer. Due to its compatibility with mobile devices, the suggested technique may find application in low-resource environments where conventional diagnostic tools may not be available. The accuracy and performance results are encouraging, confirming the system's potential to transform the diagnosis and treatment of oral cancer.

X. REFERENCES:

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