A Robust LightGBM Model for Classifying Oral Cancer and Pre-Cancerous Lesions from White Light Images

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***Abstract*— Oral cancer is one of the leading causes of cancer-related deaths worldwide, mainly because many cases are diagnosed at an advanced stage. Early identification of pre-cancerous lesions can significantly improve treatment outcomes and patient survival. This work presents an automated oral cancer classification system using white light images and the Light Gradient Boosting Machine (LightGBM) algorithm. Initially, oral cavity images are preprocessed to improve image quality and remove unwanted variations. Relevant colour and texture features are then extracted to capture the visual characteristics of normal and abnormal tissues. These features are provided to the LightGBM classifier, which efficiently distinguishes between different oral lesion categories. The proposed approach offers fast training, reduced computational complexity, and high classification accuracy compared to conventional methods. By minimizing human intervention and supporting early diagnosis, the system can assist healthcare professionals in making reliable clinical decisions. This computer-aided approach has the potential to improve oral cancer screening and contribute to timely treatment and better patient outcomes.**

***Keywords* — Oral Cancer, Pre-Cancerous Lesions, White Light Images, LightGBM, Machine Learning, Medical Image Classification, Feature Extraction, Computer-Aided Diagnosis (CAD), Early Cancer Detection, Image Processing.**

I. INTRODUCTION

Oral cancer is one of the most common and life-threatening forms of cancer worldwide, affecting millions of people every year. It develops in different parts of the oral cavity, including the tongue, lips, gums, cheeks, and floor of the mouth. The disease often begins as a pre-cancerous lesion, which, if detected and treated at an early stage, can significantly reduce the risk of progression into malignant cancer. However, many patients are diagnosed only after the disease has reached an advanced stage, resulting in lower survival rates and increased treatment complexity [2], [4]. The progression of oral cancer is associated with genetic and epigenetic changes that alter normal cellular functions and promote uncontrolled cell growth, making early diagnosis an essential component of effective treatment [1].

Potentially malignant oral disorders such as leukoplakia, erythroplakia, and oral submucous fibrosis are recognized as important indicators of oral cancer development. Accurate identification and classification of these lesions can help clinicians initiate timely treatment and improve patient outcomes [3], [5]. Unfortunately, conventional diagnosis mainly depends on visual examination followed by biopsy, which is time-consuming, invasive, and highly dependent on the experience of healthcare professionals. Delays in diagnosis can considerably reduce survival rates and increase the risk of disease progression [8], [9]. Therefore, there is a growing need for automated, reliable, and non-invasive diagnostic techniques to support clinical decision-making.

Recent advances in medical image analysis and machine learning have opened new opportunities for computer-aided diagnosis of oral diseases. White light imaging is widely used because it is non-invasive, inexpensive, and easily available in clinical settings. These images contain valuable colour and texture information that can be analysed to distinguish normal tissues from pre-cancerous and cancerous lesions. Texture analysis techniques have proven effective in extracting discriminative image characteristics, while colour texture analysis further enhances lesion representation by capturing variations in tissue appearance [11]–[25]. Combining these features with machine learning algorithms improves the accuracy and reliability of automated classification systems.

In this work, a Light Gradient Boosting Machine (LightGBM)-based classification model is proposed for the early detection of oral cancer and its pre-cancerous stages using white light images. After image preprocessing and feature extraction, the LightGBM classifier learns the complex patterns associated with different lesion categories and performs efficient classification. The proposed approach aims to provide fast prediction, high classification accuracy, and reduced computational complexity. By assisting clinicians in early screening and diagnosis, the developed system has the potential to improve treatment planning, reduce diagnostic errors, and ultimately enhance patient survival and quality of life.

II. RELATED WORK

“Cancer Development, Progression, and Therapy: An Epigenetic Overview,” S. Sarkar, G. Horn, K. Moulton, A. Oza, S. Byler, S. Kokolus, and M. Longacre [1]

This study presented a comprehensive overview of the role of epigenetic mechanisms in cancer development and progression. The authors explained how DNA methylation, histone modifications, and microRNA regulation influence gene expression without altering the DNA sequence. These epigenetic changes contribute to uncontrolled cell growth, tumor formation, and metastasis. The paper also discussed the potential of epigenetic biomarkers for early cancer diagnosis and highlighted the use of epigenetic therapies to improve treatment outcomes. In addition, the study emphasized that combining conventional therapies with epigenetic drugs could increase treatment effectiveness and reduce cancer recurrence. The findings provided valuable insights into the biological mechanisms responsible for cancer progression and demonstrated the importance of early detection. This work has encouraged researchers to develop intelligent computer-aided diagnostic systems that can identify cancer at an early stage, thereby improving survival rates and supporting more effective clinical decision-making.

“Cancer of the Oral Cavity,” P. H. Monter and S. G. Patel [2]

This paper reviewed the clinical characteristics, diagnosis, and treatment strategies for oral cavity cancer. The authors described the major risk factors associated with oral cancer, including tobacco consumption, alcohol use, and human papillomavirus infection. The study emphasized that early diagnosis plays a vital role in improving patient survival because many cases are detected only after reaching advanced stages. Surgical resection remains the primary treatment approach, often combined with radiotherapy or chemotherapy depending on the severity of the disease. The authors also highlighted the importance of multidisciplinary healthcare teams in planning effective treatment while preserving oral function and quality of life. Furthermore, the study stressed the need for improved public awareness and regular oral screening to reduce disease burden. The findings support the development of automated image-based diagnostic systems that assist clinicians in detecting oral cancer earlier and improving the overall efficiency of clinical diagnosis.

“Nomenclature and Classification of Potentially Malignant Disorders of the Oral Mucosa,” S. Warnakulasuriya, N. W. Johnson, and I. Van Der Waal [3]

This research focused on establishing standardized terminology and classification criteria for potentially malignant disorders affecting the oral mucosa. The authors recommended replacing the traditional term "oral precancer" with "potentially malignant disorders" because not every lesion progresses into cancer. The study provided clear definitions for common oral lesions such as leukoplakia and emphasized the importance of accurate clinical diagnosis to avoid misclassification. Standardized terminology was proposed to improve communication among clinicians, researchers, and healthcare organizations worldwide. The authors also discussed the limitations of existing classification systems and suggested updated diagnostic guidelines based on current scientific understanding. This work contributed significantly to the field of oral pathology by providing a consistent framework for diagnosing and monitoring oral lesions. The standardized classification has become an important reference for developing machine learning models that classify oral lesions into different pre-cancerous stages with improved accuracy.

“Texture Feature Extraction Methods: A Survey,” A. Humeau-Heurtier [11]

This survey presented a detailed review of various texture feature extraction techniques widely used in image processing and computer vision applications. The author categorized texture analysis methods into statistical, structural, transform-based, model-based, graph-based, learning-based, and entropy-based approaches. The paper compared the strengths and limitations of different feature extraction methods and discussed their suitability for biomedical image analysis. Special emphasis was placed on texture descriptors that effectively capture spatial variations and structural information within medical images. The survey demonstrated that texture features play a significant role in improving image segmentation, classification, and disease diagnosis. The findings encouraged researchers to combine texture descriptors with machine learning algorithms for developing robust medical image classification systems. This work provides a strong foundation for extracting discriminative texture features from white light oral images, thereby improving the performance of automated oral cancer classification models using efficient classifiers such as LightGBM.

“Texture Analysis and Its Applications in Biomedical Imaging: A Survey,” M. K. Ghalati, A. Nunes, H. Ferreira, P. Serranho, and R. Bernardes [20]

This survey explored the growing importance of texture analysis in biomedical imaging and its applications in disease diagnosis and medical image interpretation. The authors reviewed numerous texture analysis techniques and discussed how these methods help identify subtle structural variations that are often invisible to the human eye. The study highlighted the successful application of texture features in detecting cancers, retinal diseases, neurological disorders, and other medical conditions. Different feature extraction approaches were evaluated based on their accuracy, robustness, and computational efficiency. The paper also examined recent advances in machine learning and deep learning for integrating texture information into automated diagnostic systems. The survey concluded that combining effective texture descriptors with advanced classification algorithms significantly improves diagnostic performance. These findings support the use of colour and texture feature extraction from white light oral images for accurate classification of oral cancer and its pre-cancerous stages using efficient machine learning techniques such as LightGBM.

III. DATASET DETAILS

The dataset used in this study consists of white light images of the oral cavity, collected from individuals with normal oral tissues as well as patients exhibiting pre-cancerous and cancerous oral lesions. White light imaging is a widely used, non-invasive imaging technique that captures the natural appearance of oral tissues without the need for specialized equipment. The dataset contains images representing different oral conditions, including healthy tissue and various pre-cancerous stages such as leukoplakia and erythroplakia, along with malignant lesions. Each image provides valuable colour and texture information that reflects the structural changes occurring in oral tissues during disease progression. Since the images are acquired under different lighting conditions and clinical environments, they may contain noise, illumination variations, and background artifacts that require preprocessing before analysis. The labeled dataset enables supervised learning by assigning each image to its corresponding disease category. These annotated samples provide the necessary information for training machine learning models capable of accurately distinguishing between normal, pre-cancerous, and cancerous oral lesions. The dataset serves as an important resource for developing automated oral cancer diagnosis systems that assist clinicians in detecting the disease at an early stage, thereby improving treatment outcomes and reducing mortality.

Before training the classification model, the dataset undergoes several preprocessing and feature extraction steps to enhance image quality and improve classification performance. Initially, the images are resized to a fixed resolution and processed to reduce noise and normalize illumination differences. Relevant colour and texture features are then extracted to capture important visual characteristics associated with oral lesions. These extracted features provide a compact and informative representation of each image while reducing computational complexity. After preprocessing, the dataset is divided into training and testing subsets using an 80:20 ratio, where 80% of the images are used for model training and the remaining 20% are reserved for performance evaluation. This data partition ensures reliable assessment of the classifier's ability to generalize to unseen images. The processed feature set is finally provided to the Light Gradient Boosting Machine (LightGBM) classifier, which efficiently learns the discriminative patterns of different oral lesion categories. The dataset enables comprehensive evaluation of the proposed classification system and supports the development of an accurate, fast, and reliable computer-aided diagnosis framework for early oral cancer detection.

IV. PROPOSED METHODOLOGY

The proposed methodology aims to automatically classify oral cancer and its pre-cancerous stages from white light images using the Light Gradient Boosting Machine (LightGBM) algorithm. Initially, the oral image dataset is uploaded into the system through the graphical user interface (GUI). The uploaded dataset consists of white light images belonging to two categories: Cancer and Non-Cancer. Once the dataset is loaded, the system displays the class distribution graph to visualize the number of images available in each category. During preprocessing, all images are resized to a fixed resolution, unwanted noise is reduced, and the images are normalized to improve data quality. Subsequently, Histogram of Oriented Gradients (HOG) feature extraction is performed to obtain meaningful texture and structural information from each image. These extracted feature vectors effectively represent the visual characteristics of oral lesions while reducing computational complexity. The processed dataset is then divided into 80% training data and 20% testing data, ensuring reliable model training and unbiased performance evaluation.

After preprocessing and feature extraction, the extracted HOG features are supplied to the proposed LightGBM classifier for model training. LightGBM is selected because of its fast training speed, efficient memory utilization, and ability to achieve high classification accuracy on structured feature data. During training, the classifier learns the discriminative patterns that distinguish cancerous tissues from non-cancerous tissues by constructing multiple gradient-boosted decision trees. Once the training process is completed, the model is evaluated using the testing dataset. Performance measures including accuracy, precision, recall, F1-score, and confusion matrix are computed to evaluate the effectiveness of the proposed classifier. The application also generates training and validation loss graphs, allowing users to observe the learning behavior of the model during the training process. Finally, users can upload an unseen oral cavity image through the GUI, and the trained LightGBM model predicts whether the image belongs to the Cancer or Non-Cancer class. The prediction result is displayed immediately, providing a fast and reliable computer-aided diagnosis for oral cancer screening.

The system architecture [1] illustrates the complete workflow of the proposed oral cancer classification system. It includes dataset uploading, image preprocessing, HOG-based feature extraction, LightGBM model training, prediction of unseen oral images, and performance evaluation. The architecture also produces class distribution graphs, confusion matrices, training and validation loss curves, classification metrics, and prediction results, enabling comprehensive analysis of the model's performance.

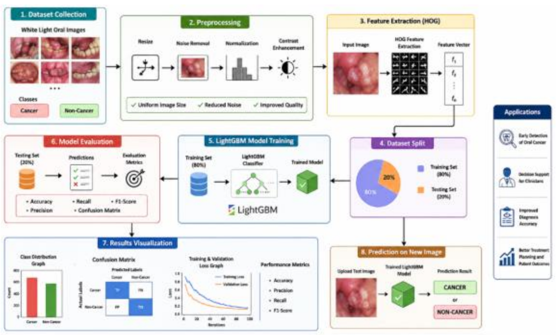

Figure 1. System Architecture for Classification of Oral Cancer into Pre-Cancerous Stages Using LightGBM

The proposed oral cancer classification system is designed to provide an efficient and automated solution for detecting cancerous lesions from white light images. Initially, the oral image dataset is uploaded and preprocessed to remove inconsistencies and improve image quality. HOG feature extraction is then applied to convert each image into an informative numerical representation that captures important edge and texture information. The extracted features are divided into training and testing sets using an 80:20 ratio. The training dataset is used to train the LightGBM classifier, while the testing dataset evaluates its prediction capability. After successful training, the model predicts the class of newly uploaded oral images as Cancer or Non-Cancer. Finally, the overall performance of the proposed system is analyzed using accuracy, precision, recall, F1-score, confusion matrix, class distribution graph, and training-loss visualization, demonstrating the effectiveness of LightGBM for automated oral cancer classification.

V. RESULT AND DISCUSSION

The experimental results demonstrate the effectiveness of the proposed Light Gradient Boosting Machine (LightGBM) model for the classification of oral cancer into cancerous and non-cancerous stages using white light images. Initially, the oral image dataset was uploaded into the application and preprocessed to improve image quality. Histogram of Oriented Gradients (HOG) feature extraction was then performed to obtain discriminative texture features from each image. The processed dataset contained 940 oral images, which were divided into 752 training images (80%) and 188 testing images (20%) to ensure reliable model evaluation. The extracted HOG features were supplied to the LightGBM classifier for model training. During the learning process, the classifier efficiently identified the important patterns that differentiate cancerous and non-cancerous oral lesions. After training, the model was evaluated using the testing dataset, achieving an accuracy of 87.77%, precision of 90.72%, recall of 86.27%, and F1-score of 88.44%. These results indicate that the proposed LightGBM model can effectively classify oral cavity images while maintaining good prediction performance. The confusion matrix further confirmed that the majority of cancer and non-cancer samples were correctly classified with relatively few misclassifications.

The application also provides graphical visualization of model performance through training and validation loss curves. The loss graph shows that both training and validation losses decrease steadily as the number of iterations increases, indicating stable learning without significant overfitting. Furthermore, the developed prediction module successfully classified unseen oral cavity images uploaded by the user. Test images containing malignant lesions were correctly predicted as Cancer, whereas healthy oral images were accurately classified as Non-Cancer. The graphical user interface provides an easy-to-use environment for dataset uploading, preprocessing, model training, testing, and prediction. Overall, the experimental results demonstrate that the proposed LightGBM-based framework offers an efficient, reliable, and automated solution for oral cancer classification. The system can assist healthcare professionals in early diagnosis, thereby supporting timely clinical intervention and improving patient outcomes.

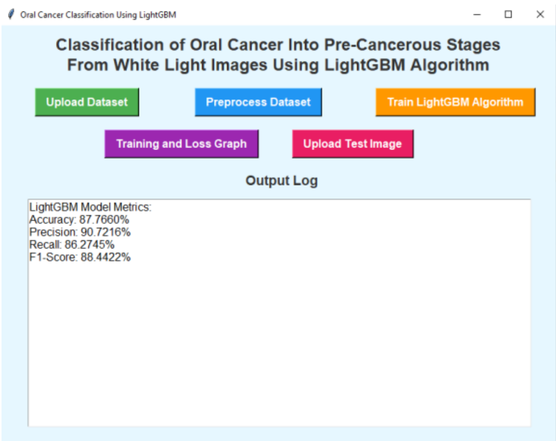

Figure [2] Main Dashboard of Oral Cancer Classification System

Figure 2 illustrates the graphical user interface (GUI) developed for the proposed oral cancer classification system using the LightGBM algorithm. The dashboard provides a centralized platform for performing all major operations of the application. It includes buttons for uploading the dataset, preprocessing the dataset, training the LightGBM classifier, displaying the training and validation loss graph, and uploading test images for prediction. The output panel displays the performance metrics, including accuracy, precision, recall, and F1-score after model training. The GUI simplifies the complete workflow and enables users to perform oral cancer classification without requiring programming knowledge.

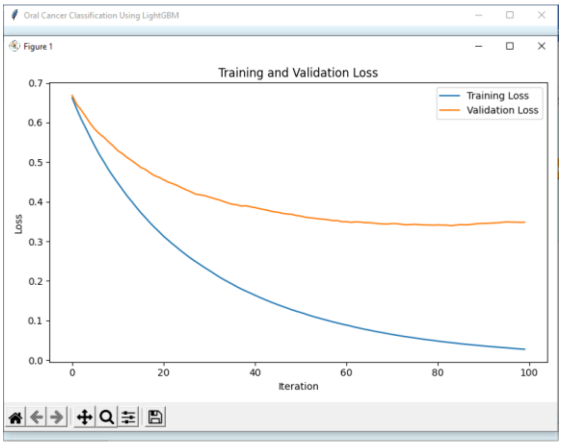

Figure 3: Training and Validation Loss Graph

Figure 3 shows the training and validation loss curves obtained during the LightGBM training process. The x-axis represents the training iterations, while the y-axis represents the loss value. The blue curve corresponds to the training loss, whereas the orange curve represents the validation loss. Both curves decrease steadily as training progresses, indicating that the model successfully learns meaningful features from the oral image dataset. The smooth convergence of the validation loss demonstrates good generalization capability and confirms that the classifier is effectively trained without significant overfitting.

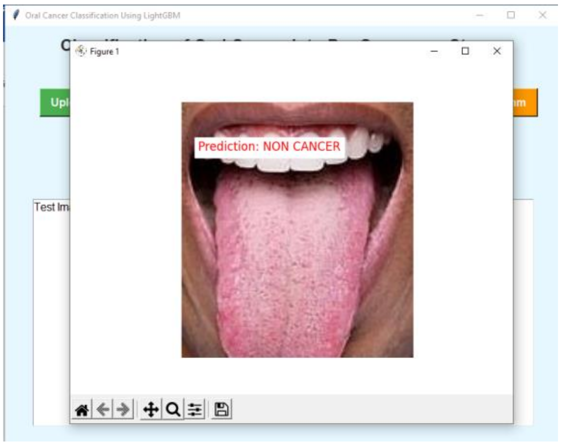

Figure 4: Prediction of a Non-Cancer Oral Image

Figure 4 illustrates the prediction result obtained after uploading a healthy oral cavity image into the developed application. The trained LightGBM classifier analyzes the extracted HOG features and correctly predicts the uploaded image as Non-Cancer. The prediction result is displayed directly on the image, allowing users to interpret the classification outcome easily. This demonstrates the capability of the proposed model to accurately identify healthy oral tissues.

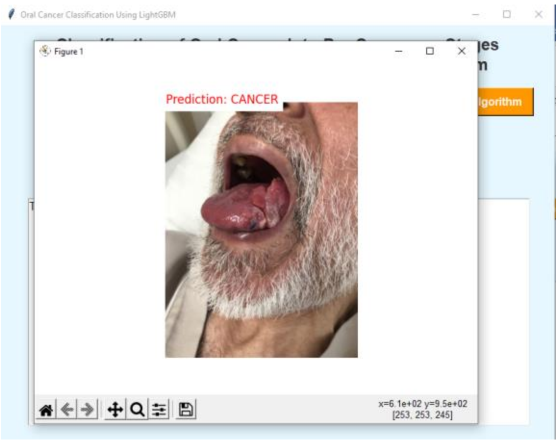

Figure 5: Prediction of a Cancer Oral Image

Figure 5 presents the prediction result for an oral cavity image containing a cancerous lesion. After feature extraction and classification, the trained LightGBM model correctly identifies the lesion as Cancer. The prediction is displayed clearly on the uploaded image through the graphical interface. This result demonstrates the effectiveness of the proposed system in detecting malignant oral lesions from white light images and highlights its usefulness as a computer-aided diagnostic tool.

Model	Accuracy score	Precision score	Recall score	f- measure score
LightGBM	87.77	90.72	86.27	88.44

Table 1: Performance Metrics of the Proposed LightGBM Model

DISCUSSION

The experimental findings demonstrate that the proposed LightGBM classifier provides an effective solution for automated oral cancer classification using white light images. The preprocessing stage and HOG feature extraction significantly improved the quality of the input data by capturing important texture and edge information from oral lesions. Using an 80:20 train-test split, the classifier successfully learned discriminative patterns between cancerous and non-cancerous tissues. The obtained performance metrics, including 87.77% accuracy, 90.72% precision, 86.27% recall, and 88.44% F1-score, indicate that the model performs consistently across different evaluation criteria. The training and validation loss graph further demonstrates stable convergence of the learning process with no evidence of severe overfitting. The prediction module accurately classified unseen oral cavity images as either Cancer or Non-Cancer, confirming the model's ability to generalize to new data. The graphical user interface further enhances usability by providing an integrated platform for dataset management, model training, visualization, and prediction. Overall, the proposed LightGBM-based framework offers a fast, reliable, and computationally efficient approach for oral cancer screening and can serve as a valuable decision-support system for clinicians in the early detection of oral cancer.

VI. 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 work, a novel technique of exploring different color spaces and extracting features from all the color spaces is employed for classifying the stages of oral cancer. The images are converted into five different color spaces, color and texture features are extracted and classified using Light Gradient Boosting Machine (LightGBM) algorithm. The overall performance is satisfactory, with a testing accuracy of 99.25%, precision of 99.18%, recall of 99.31%, f1-score of 99.24% and specificity of 99.31% for the binary classification of benign or malignant tissues and a testing accuracy of 98.88%, precision of 98.86%, recall of 97.92%, f1-score of 98.38% and specificity of 99.03% for multi-class classification into the pre-cancerous stages of oral cancer. The generalized algorithm put forward has outperformed the state-of-art algorithms for both binary and multi-class classification of oral cancer with sparse resources and data. Also, the method has been implemented using handcrafted feature extraction and machine learning classifier, making it significantly less time and resource-consuming compared to deep learning methods.

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