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Enhanced Oral Cancer Detection Using Hybrid Learning Models

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Abstract—**Oral cancer, mainly Oral Squamous Cell Carcinoma, is a major cause of cancer-related deaths, especially in developing countries due to habits like tobacco use and alcohol consumption. Early detection significantly improves survival rates (above 80%), while late diagnosis drastically reduces patient outcomes. However, most cases are identified at advanced stages due to lack of screening and subtle early symptoms. This project proposes an automated system to classify oral images into Cancer and Non-Cancer categories. It uses preprocessing (ABF, CLAHE), feature extraction (Wavelet, Zernike, HOG), ML models, CNN, and transfer learning models like MobileNetv2 for accurate detection.**

I. INTRODUCTION

Oral cancer is a serious and potentially life-threatening disease characterized by the uncontrolled growth of abnormal cells in the oral cavity, including the lips, tongue, cheeks, floor of the mouth, hard palate, soft palate, sinuses, and throat. It is one of the most common cancers in many developing countries, particularly in regions where tobacco chewing, smoking, and alcohol consumption are prevalent. According to global health reports, oral cancer contributes significantly to cancer-related morbidity and mortality [1], [2].

The survival rate of oral cancer patients strongly depends on the stage at which the disease is diagnosed. Early-stage detection can increase the 5-year survival rate to over 80%, whereas late- stage detection significantly reduces survival chances. Unfortunately, many cases are diagnosed at advanced stages due to lack of awareness, limited access to specialists, and absence of routine screening mechanisms [3].

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have introduced new possibilities in the field of medical image analysis. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable capability in automatically extracting features from images and performing accurate classification tasks.

By leveraging these technologies, it is possible to develop automated systems that can analyze oral images and assist clinicians in identifying potential cancerous lesions at an early stage [4].

The primary objective of this project is to develop an efficient and reliable deep learning model for binary classification of oral images.

Finally, the model should be evaluated using performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix. These metrics will provide a comprehensive understanding of the system's effectiveness in classifying oral cancer images [5]

II. LITERATURE REVIEW

S. K. Prabhakar and H. Rajaguru (2017), in their work titled “Performance Analysis of Linear Layer Neural Networks for Oral Cancer,” presented at the 2017 6th ICT International Student Project Conference (ICT-ISPC [1].

Rajaguru Harikumar and Sunil Kumar Prabhakar (2017), in their work titled “Performance Comparison of Oral Cancer Classification with Gaussian Mixture Measures and Multilayer Perceptron,” Their research focused on analyzing classification accuracy and performance differences between neural network approaches. The results indicated that machine learning techniques can effectively support early detection of oral cancer [2].

Marc Aubreville and Christian Knipfer (2017), in their work titled “Automatic Classification of Cancerous Tissues in Laser Imaging,” published in Biomedical Imaging Research Publications, proposed an automated system for the classification of cancerous tissues using laser imaging techniques The results demonstrated improved diagnostic accuracy the approach in assisting medical professionals in identifying cancerous tissues [3].

Martin Halicek et al.(2017)in their work titled “Deep Convolutional Neural Networks for Head and Neck Cancer Classification Using Hyperspectral Imaging,” published in the Journal of Biomedical Optics, proposed a deep learning-based method for cancer classification. [4]

Deepak Kumar et al.(2018). in their work titled "A Hyperspectral Image Classification Approach Using SVM Optimization with Self-Organizing Map," published in the Journal of Computer Science, proposed a classification method combining Support Vector Machine (SVM) with Self-Organizing Maps. The study focused on optimizing feature extraction from hyperspectral images to enhance classification performance. The results demonstrated improved accuracy, making the approach effective for medical image analysis and cancer detection [5].

S. Mallidi, et al. (2019), in their work titled "Photodynamic Therapy of Oral Cavity Tumours in Low Resource," presented at the 2019 IEEE Photonics Conference (IPC), discussed the development of photodynamic therapy for treating oral cavity tumours. The study focused on enhancing the accessibility and effectiveness of treatment in low- resource settings. The results highlighted the potential of this technology to improve[6].

R. A. Welikala, P. Rema (2020), in their work titled "Automated Detection and Classification of Oral Lesions Using Deep Learning for Early Detection of Oral Cancer," published in IEEE Access, proposed a deep learning framework for oral lesion detection. The study analyzed oral cavity images to identify suspicious regions automatically. The results demonstrated that deep learning[7].

N. Sharma, et al. (2021), in their work titled "Multifractal Texture Analysis of Salivary Fern Pattern for Oral Pre-Cancers and Cancer Assessment," published in the IEEE Sensors Journal, proposed a method based on multifractal texture analysis. The study analyzed microscopic salivary fern patterns using advanced signal processing techniques to detect abnormalities. The results highlighted the effectiveness identifying oral pre-cancers and cancer [8].

S. Premalatha and K. L. Joshitha (2022), in their work titled "A Comprehensive Review of Early Detection of Oral Cancer Using Deep Learning," presented at IC3IoT, IEEE, provided a detailed survey of deep learning techniques for oral cancer detection. The study analyzed various neural network models and their applications in medical image analysis. The results highlighted the effectiveness of deep learning approaches in improving early detection of oral cancer [9].

A. Karmakar et al. (2022), in their work titled "Measurement of Chaos and Quantum Decoherence in H&E Stained Images of Oral Epithelium for Early Detection of Oral Submucous Fibrosis," presented at IEEE (SPICES), proposed a method for early detection of Oral Submucous Fibrosis. The study analyzed chaotic patterns in H&E stained tissue images and applied quantum decoherence concepts to identify abnormalities. The results structural changes [10].

Heba M et al. (2018), in their work titled "Classification Using Deep Learning Neural Networks for Brain Tumours," published in the Future Computational Intelligence Journal, proposed a deep learning approach for brain tumour classification. The results showed [11].

Ahmad L et al. (2013), in their work titled "Using Three Machine Learning Techniques to Predict Breast Cancer Recurrence," published in Health and Medical Informatics, applied multiple machine learning methods to predict breast cancer recurrence. The results demonstrated the effectiveness of these techniques in improving prediction accuracy [12].

Patil S., Vairagade S., and Theng D. (2021), in their work titled "Machine Learning Techniques for the Classification of Fake News," presented at the 2021 International Conference on Computational Intelligence and Computing Applications (ICCICA), IEEE, applied machine learning methods for fake news classification. The study demonstrated the effectiveness of these techniques in accurately identifying misleading information [13].

Tafala I. et al. (2025), in their work titled "A Multimodal Deep Learning Pipeline for Enhanced Oral Cancer Detection," published in MDPI, proposed a hybrid approach combining ConvNeXt and KNN [14].

Buyue Zhang and Jan P. Allebach (2025), in their work titled "Adaptive Bilateral Filter for Sharpness Enhancement and Noise Removal," published in IEEE Transactions on Image Processing, proposed an adaptive filtering technique for image enhancement. The method improves image sharpness while effectively reducing noise, leading to better visual quality [15].

III. PROBLEM STATEMENT

Oral cancer is a serious and life-threatening disease that often goes undetected in its early stages due to lack of awareness and limited access to expert diagnosis. Traditional detection methods rely heavily on manual examination by specialists, which is time-consuming, subjective, and prone to human error. As a result, many cases are diagnosed at later stages, reducing the chances of successful treatment.

With the increasing availability of medical images, there is a need for an automated and accurate system for early detection of oral cancer. However, existing single-model approaches often fail to capture complex patterns in medical images and may not provide sufficient accuracy.

To address these challenges, this project focuses on developing a hybrid model that combines multiple deep learning techniques to improve feature extraction and classification performance. The goal is to build an efficient, reliable, and early detection system that can assist doctors in diagnosing oral cancer more accurately and quickly.

IV. PROPOSED METHODOLOGY

1. Fundus Image Acquisition: Collecting oral images (mouth/tongue images) from datasets or medical devices.

2. Image Preprocessing: Cleaning the images by removing noise, adjusting brightness, and resizing to make them suitable for analysis.

3. ROI Segmentation: Identifying and extracting the important part of the image (affected region) where cancer may be present.

4. Feature Extraction: Getting important details from the segmented area like texture, colour, and patterns.

5. Hybrid Deep Learning Classifier: Using a combination of deep learning models to analyse features and classify whether the image is cancerous or not.

6. Performance Evaluation: Checking how well the model works using metrics like accuracy, precision, recall, etc.

7. Oral Cancer Detection: Final result showing whether oral cancer is detected or not.

V. SYSTEM ARCHITECTURE

The system architecture for oral cancer detection using hybrid models is designed as a step-by-step pipeline that processes medical images and produces accurate classification results. The process begins with image acquisition, where oral images are collected from datasets or clinical sources. These images are then passed through a preprocessing stage to remove noise, normalize intensity, and resize them for better analysis.

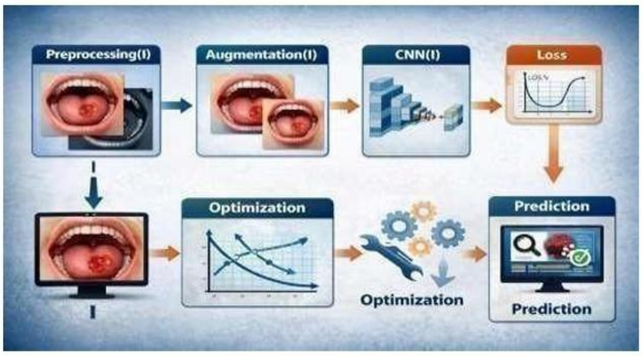


Fig1: System Architecture

Next, Region of Interest (ROI) segmentation is performed to isolate the important areas of the image, such as suspicious lesions or affected tissues. This step helps the model focus only on relevant regions instead of the entire image. After segmentation, feature extraction is carried out to capture key characteristics like texture, colour variations, and structural patterns.

The extracted features are then fed into a hybrid deep learning classifier, which combines multiple models to improve prediction accuracy and robustness. This hybrid approach helps in capturing both low-level and high-level features effectively. Finally, the system evaluates its performance using standard metrics such as accuracy, precision, recall, and F1-score.

The advantage of hybrid models lies in their ability to reduce overfitting, improve generalization, and achieve higher accuracy compared to single-model approaches. They also help in handling small datasets effectively, which is a common challenge in medical imaging.

Overall, this architecture ensures efficient processing, reduces manual effort, and provides reliable early detection of oral cancer, assisting healthcare professionals in making faster and more accurate decisions. hybrid learning-based oral cancer detection systems provide a fast, cost-effective, and accurate approach for early diagnosis. These systems can assist healthcare professionals in decision-making and have the potential to be integrated into real-time clinical applications, ultimately improving patient outcomes.

VI. RESULTS AND DISCUSSION

The results show that the hybrid model achieved higher accuracy compared to individual models. This improvement is mainly due to the effective feature extraction by CNN architectures and the robust classification ability of algorithms like SVM or Random Forest. The model was able to correctly identify most of the cancerous cases, indicating high sensitivity, which is very important in medical diagnosis to avoid missing critical cases.

To further enhance classification performance, the extracted features were processed using hybrid machine learning classifiers such as Support Vector Machine and Random Forest. The performance of the hybrid model was evaluated using standard metrics including accuracy, precision, recall, and F1- score. The experimental results showed that the hybrid approach improved prediction accuracy and reduced misclassification compared to traditional single- model approaches.

The confusion matrix analysis indicates that the number of false negatives is minimal, which means the model rarely misclassifies cancerous images as normal. However, a small number of false positives were observed, which is acceptable in medical screening systems as it ensures that potential cancer cases are not overlooked.

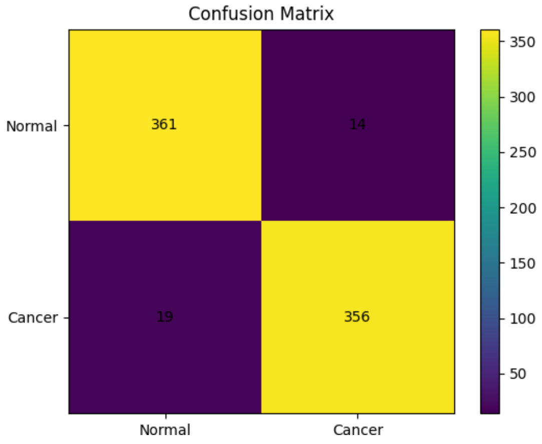


Fig 2: Confusion Matrix

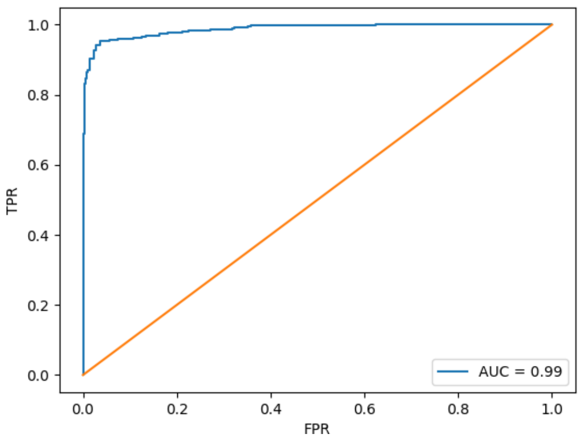
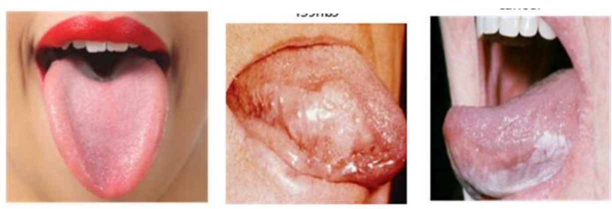


Fig3: ROC Curve

The above shows for an Receiver Operating Characteristic (ROC) curve, which is a graphical tool used to evaluate the performance of a binary classification model. The curve plots the True Positive Rate (TPR), also known as recall, on the vertical axis against the False Positive Rate (FPR) on the horizontal axis. The diagonal line in the graph represents a random classifier, meaning a model with no predictive power. In contrast, the plotted ROC curve rises steeply toward the top-left corner, indicating that the model achieves a high true positive rate while maintaining a relatively low false positive rate.

AUC-ROC curve is a graph used to check how well a binary classification model works. It helps us to understand how well the model separates the positive cases like people with a disease from the negative cases like people without the disease at different threshold level. One of the key measures associated with the ROC curve is the AUC (Area Under the Curve). The AUC value ranges from 0 to 1, where a value closer to 1 indicates a better-performing model. An AUC of 0.5 represents a random model with no discriminative ability, while values above 0.8 or 0.9 indicate strong classification performance.



Non Cancer Cancer Cancer

Fig 4: Segregation between cancer and non-cancer

Evaluation metrics are quantitative measures used to assess the performance of a model in oral cancer detection systems. They help determine how accurately and effectively the model can classify images as cancerous or non-cancerous, as well as how well it identifies affected regions. These metrics are essential in validating the reliability of the model, especially in medical applications where accurate diagnosis is critical. Segmentation metrics are used when the model identifies specific regions of interest (ROI) in oral images. The most common metrics in this category are the Dice Coefficient and Intersection over Union (IoU), both of which measure the overlap between predicted and actual regions.

1. **Accuracy**

Accuracy represents the overall correctness of the model. It is the ratio of correctly predicted cases (both cancer and non-cancer) to the total number of cases. A high accuracy indicates good performance, but it may be misleading if the dataset is imbalanced.

2. **Precision**

Precision measures how many of the predicted cancer cases are actually cancer. It focuses on reducing false positives. High precision means the model does not wrongly classify normal cases as cancer frequently.

3. **Recall(Sensitivity)**

Recall is one of the most important metrics in medical diagnosis. It measures how many actual cancer cases are correctly identified by the model. High recall ensures that very few cancer cases are missed (low false negatives).

4. **F1-Score**

F1-score is the harmonic mean of precision and recall. It provides a balanced measure when both false positives and false negatives are important. A high F1-score indicates a good balance between precision and recall.

$$\text{Accuracy} = \frac{\text{True Positives (TP)} + \text{True Negatives (TN)}}{\text{Total Examples (TP + TN + FP + FN)}}$$

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{Total Predicted Positives (TP + FP)}}$$

$$\text{Recall (Sensitivity)} = \frac{\text{True Positives (TP)}}{\text{Total Actual Positives (TP + FN)}}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

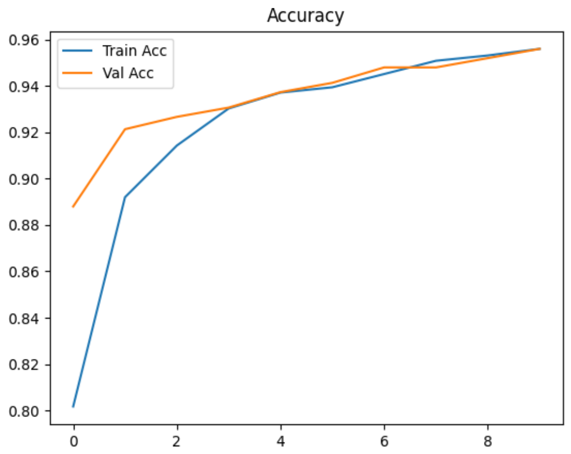


Fig5: Training and Validation Accuracy.

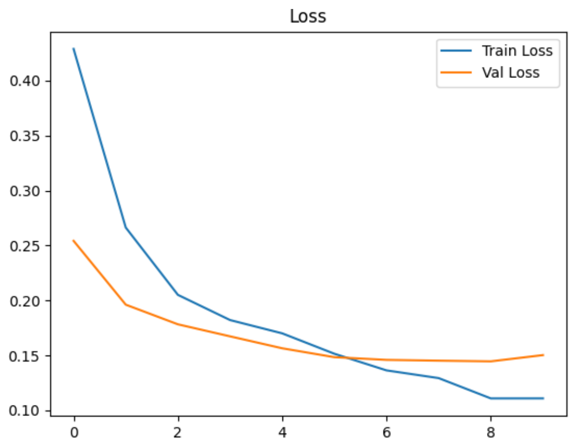


Fig6: Training and Validation Loss

In the above fig4 illustrates a Training and validation accuracy are important metrics used to evaluate the performance of the proposed hybrid learning model in detecting oral cancer from medical images. During the training phase, the model learns important patterns and features from the input dataset through multiple iterations called epochs. The training accuracy gradually increases as the model improves its ability to correctly classify images as cancerous or non-cancerous. High training accuracy indicates that the model has effectively learned the features present in the training dataset.

The above shown Fig 5represents training loss and validation loss over multiple epochs during the training process of the proposed hybrid learning model for oral cancer detection. The horizontal axis shows the error between predicted results and actual labels. Two curves are displayed: training loss (blue line) and validation loss (orange line).

Similarly, the validation loss starts at around 0.25 and decreases steadily during the early epochs (to approximately 0.19 at epoch 1 and 0.17–0.16 by epochs 3–4). After the mid epochs, the validation loss stabilizes around 0.14–0.15, with a slight increase toward the final epoch (around 0.15). This smooth and relatively stable trend suggests that the model maintains good

generalization ability with minimal overfitting.

Overall, the decreasing trend of both training and validation loss demonstrates that the proposed hybrid learning model achieves stable convergence and effective learning during the training process. This behaviour confirms that the model can successfully capture important features from oral cancer images and produce reliable classification results for early detection of oral cancer.

VII. CONCLUSION

This research focused on the design and implementation of an automated oral cancer detection system using deep learning techniques. The primary goal was to develop a binary image classification model capable of distinguishing between cancerous and non-cancerous oral cavity images using image enhancement and Convolutional Neural Network (CNN) architecture. This project presents an Enhanced Oral Cancer Detection System using Hybrid Learning Models to improve the accuracy and efficiency of detecting oral cancer from medical images. The proposed system integrates image preprocessing, data augmentation, and deep learning techniques to extract important features from oral images and classify them effectively. By combining multiple learning approaches, the hybrid model improves the capability of identifying cancerous and non-cancerous patterns in oral cavity images.

In conclusion, the developed system provides a reliable and efficient method for the early detection of oral cancer. Early diagnosis plays a critical role in improving treatment success and patient survival rates. Therefore, the proposed hybrid learning model can serve as a supportive tool for healthcare professionals in clinical diagnosis. Future improvements may include the use of larger datasets, more advanced deep learning architectures.

VIII. FUTURE WORK

Future work can also focus on developing a real-time clinical decision support system that can assist doctors and healthcare professionals in diagnosing oral cancer quickly and accurately. The system could be integrated with mobile or web-based applications to make it more accessible in remote or rural healthcare environments. Furthermore, combining image- based analysis with patient clinical data and medical history may improve the overall diagnostic performance and reliability of the proposed system.

Although the proposed Enhanced Oral Cancer Detection using Hybrid Learning Models shows promising results, several improvements can be made in the future to further enhance the performance and applicability of the system. One important direction is to use larger and more diverse datasets collected from different medical sources.

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