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AI-Based Oral Cancer Detection Using Hybrid Deep Learning Models

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Abstract: The rising incidence and mortality rates of oral cancer have turned it into a significant global public health concern. Detecting the condition at an early stage is essential for achieving better health outcomes, as timely intervention significantly boosts the chances of effectively treating conditions such as Squamous Cell Carcinoma, Lymphoma, Melanoma, Kaposi's Sarcoma, Osteosarcoma, and Adenoid Cystic Carcinoma. This proposal presents an AI-driven system designed to detect oral cancer through hybrid deep learning models. By integrating the EfficientNet and XceptionNet frameworks, the system autonomously extracts pertinent features from medical images and categorizes them as either cancerous or non-cancerous. The method utilizes a comprehensive dataset of oral cancer images, encompassing various lesion types, Gathered via clinical imaging techniques, including digital photography . The proposed system seeks to enhance the precision, dependability, and speed of oral cancer detection, providing a non-invasive tool to aid in early diagnosis and clinical decision-making.
Keywords: Detection of Oral Cancer, Deep Learning Techniques, CNN Models, EfficientNet Architecture, XceptionNet Architecture, Image-Based Diagnosis, Hybrid System, Early Intervention.

I. INTRODUCTION

Oral cancer stands as one of the most widespread and life-threatening malignancies affecting populations globally.Delays in diagnosing oral cancer often result in higher mortality and increased complications. About half of all cases occur in South Asia, and two-thirds of all cases occur in low- and middle-income countries. Tobacco use and excessive alcohol intake are considered the leading contributors to the development of oral cancer. Among nations with moderate to low income levels, survival rates remain low as many individuals present with oral lesions only at advanced stages. Treating cancer, particularly in its advanced stages, can be extremely costly.

Delayed diagnosis is often the result of limited awareness about oral lesions among both medical professionals and patients.The screening program has Emphasized the diagnosis of OPMD, as these conditions pose a significant risk of malignant transformation, its enormous value in reducing mortality and morbidity from oral malignancies, and its prevalence.Oral cancer, encompassing malignancies of the lips, tongue, cheeks, floor of the mouth, palate, sinuses, and throat, represents and Contributes greatly to global morbidity and mortality, making it a pressing healthcare issue. Recognizing the disease in its early stages leads to improved patient outcomes and higher treatment success, yet Modern-day diagnosis still depends heavily on the subjective expertise of clinicians, which can vary widely.This research focuses on harnessing deep learning advancements to design a robust system capable of accurately detecting oral cancer from medical imaging data., utilizing the powerful convolutional neural network architectures of XceptionNet and EfficientNet.

II. RELATED WORK

Many researchers have actively investigated The impact of AI on improving oral cancer detection methods. Early studies explored the biological mechanisms and pathways involved acting as the cornerstone for the implementation of AI solutions in oral squamous cell carcinoma diagnosis [1]. Advances in deep learning—particularly through Convolutional Neural Networks (CNNs)—have significantly improved the precision of lesion identification.

To enhance detection performance in biomedical imaging, various models, including fusion strategies and transfer learning frameworks like EfficientNet and XceptionNet, have been successfully adopted [2], [3]. Recent developments emphasize the effectiveness of ensemble deep learning methods in boosting both accuracy and consistency when diagnosing oral cancer [3]. Building on these innovations, the present work introduces an AI-based approach that integrates EfficientNet and XceptionNet for accurate and non-invasive detection of oral cancer from medical images.

III. METHODOLOGY

The proposed system includes:

A. Data Collection

Images sourced from medical imaging datasets. The dataset used in this study was obtained from the Kaggle open-source platform, which contains publicly available oral cavity images. The dataset comprises over 2000 annotated medical images representing both cancerous and non-cancerous oral conditions.Total images**:**2,000+

Class distribution:

- Cancerous:1,200images
- Non-cancerous:800images

These images are provided in **.**jpg and **.**png formats, with varying resolutions. For consistent preprocessing, all images were standardized to a resolution of 256 × 256 pixels. The dataset was split into three subsets for training and evaluation:

Trainingset:70% and Validationset:15%,Testingset:15%. This distribution ensures balanced exposure to data across model training and evaluation phases while preventing data leakage.

B. Preprocessing

The preprocessing pipeline aims to enhance visual details and ready the data for efficient feature extraction.. The workflow incorporates the following steps:

1) *Grayscale Conversion*: All images are converted to grayscale to reduce computational complexity and focus on the intensity information relevant to lesion detection, eliminating unnecessary color channels.
2) *Contrast Enhancement & Noise Removal*: To address varying lighting conditions and image clarity, contrast enhancement techniques The system applies adaptive histogram equalization techniques for better image preprocessing. Gaussian filtering is utilized for reduce noise and smooth the images while preserving important edges.
3) *Thresholding***:** Thresholding helps in segmenting the region of interest through the binarization of grayscale images. thresholding is used to automatically determine a calculated threshold to effectively separate foreground lesions from the background.
4) *Histogram Equalization***:** This strategy is adopted to normalize image brightness and improve contrast, especially in underexposed or overexposed areas, thus enhancing the visibility of lesions.
5) *Watershed Segmentation:* Finally, the watershed algorithm is used for precise boundary detection of lesions. It treats grayscale images as topographic surfaces and identifies the edges of regions based on intensity gradients, allowing accurate separation of lesion areas from surrounding tissues.

C. Feature Extraction

Feature extraction Feature extraction is carried out using transfer learning-based deep CNN models. Specifically, XceptionNet and EfficientNet architectures are utilized, both pre-trained on the Image Net dataset to leverage rich, general-purpose feature representations. During training, the initial convolutional layers of both models are frozen to preserve the learned low-level features (such as edges, textures, and simple patterns), while the higher-level layers are fine-tuned on the oral cancer dataset to adapt the models to domain- specific features. The approach effectively combines speed and computational resource management with improved performance on the target task.

The output features from both networks are concatenated and passed to the hybrid optimization stage for further refinement and classification.

D. Classification

The The final classification stage uses a A deep learning framework developed to perform automatic extracts features from preprocessed images and classifies them into cancerous and non-cancerous categories. We employ hybrid architectures combining EfficientNet and XceptionNet, both leveraging transfer learning and fine-tuning to enhance performance. The output layer is designed with two nodes contains two neurons corresponding to the cancerous and non-cancerous classes, utilizing a Softmax activation function to compute class probabilities.Categorical cross-entropy was selected as the loss function, and the Adam optimizer was used to achieve reliable convergence during training. .

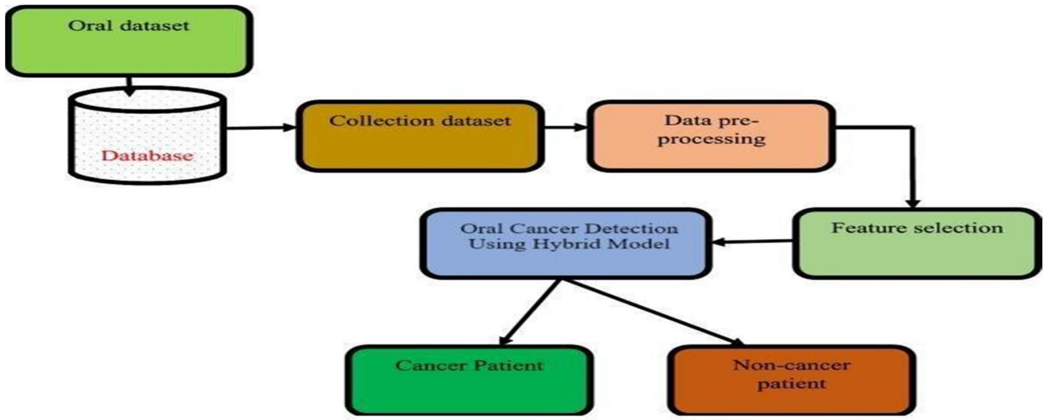

Fig 1. Architecture of Oral Cancer Detection System

The system design refers to the process of translating requirements into a structure that can be physically implemented. Various design features are followed to develop the system the design specification describes the features of the system, the opponent or elements of the system and their appearance to the end-users. The image will be resized to 256x256 pixels.A combination of XceptionNet and EfficientNet is used to train the model and predict whether a lesion is cancerous or non-cancerous. The infected area can detected using watershed image segmentation algorithm.

IV. IMPLEMENTATION

The implementation of the system was carried out in Python. Image preprocessing tasks, such as noise reduction and contrast enhancement, were performed using OpenCV. The proposed hybrid To ensure accurate classification with reduced risk, the model incorporates XceptionNet and EfficientNet through transfer learning and fine-tuning risk of overfitting.

V. RESULTS AND ANALYSIS

The model's performance was evaluated using a dataset of annotated oral cancer images, with metrics used to measure its effectiveness:

The ensemble deep learning technique introduced was assessed using a test set of oral cavity images.

Metric	Value(%)
Accuracy	92.7
Sensitivity	91.3
Specificity	94.1
F1Score	93.0

Table 1. Performance outcomes of the developed hybrid classification system

To provide evidence of the hybrid approach's effectiveness, Table 2 contrasts the Diagnostic performance of the hybrid model with a standard CNN baseline that was trained without optimization or model fusion.

Model	Accuracy(%)	Sensitivity(%)	Specificity(%)	F1Score(%)
Standard CNN(baseline)	85.4	83.0	87.2	84.0
Proposed Hybrid Model	92.7	91.3	94.1	93.0

Table 2. Comparative analysis of model performance.

The Performance deviation during training and validation and accuracy curves exhibited smooth convergence without signs of overfitting, Revealing the strength of the hybrid system optimization effectively adjusted the model to generalize well on new data. Compared to standard CNN models, the hybrid model notably enhanced prediction quality. Analysis of the training curves demonstrated steady convergence while effectively avoiding overfitting.

This section provides a snapshot of Oral Cancer, explaining the application's key pages with accompanying page snapshots.

1) Home Page

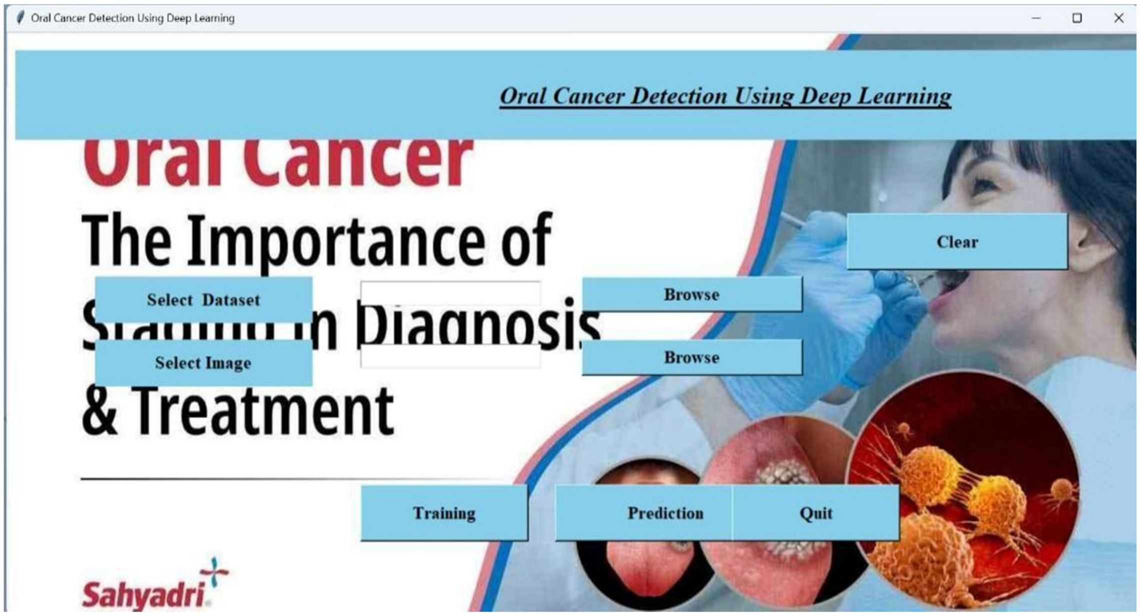

Fig 2: Snapshot—HomePage

2) Folder Selecting Page For Training

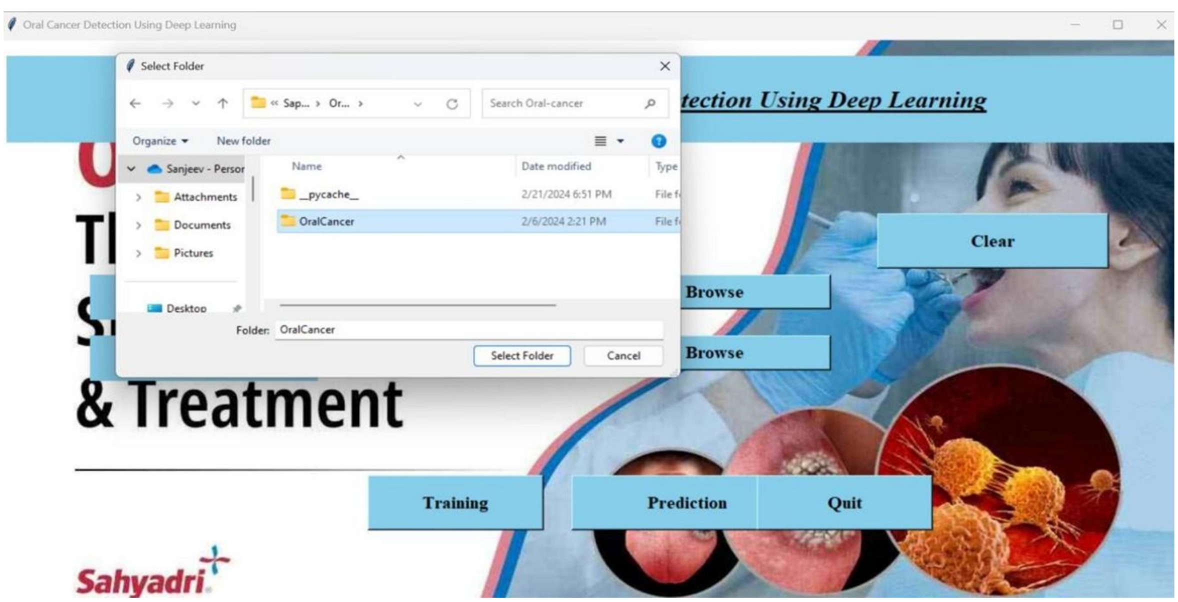

Fig 3: Snapshot—Folder Selection Page

3) *Images Selection Page For Prediction*

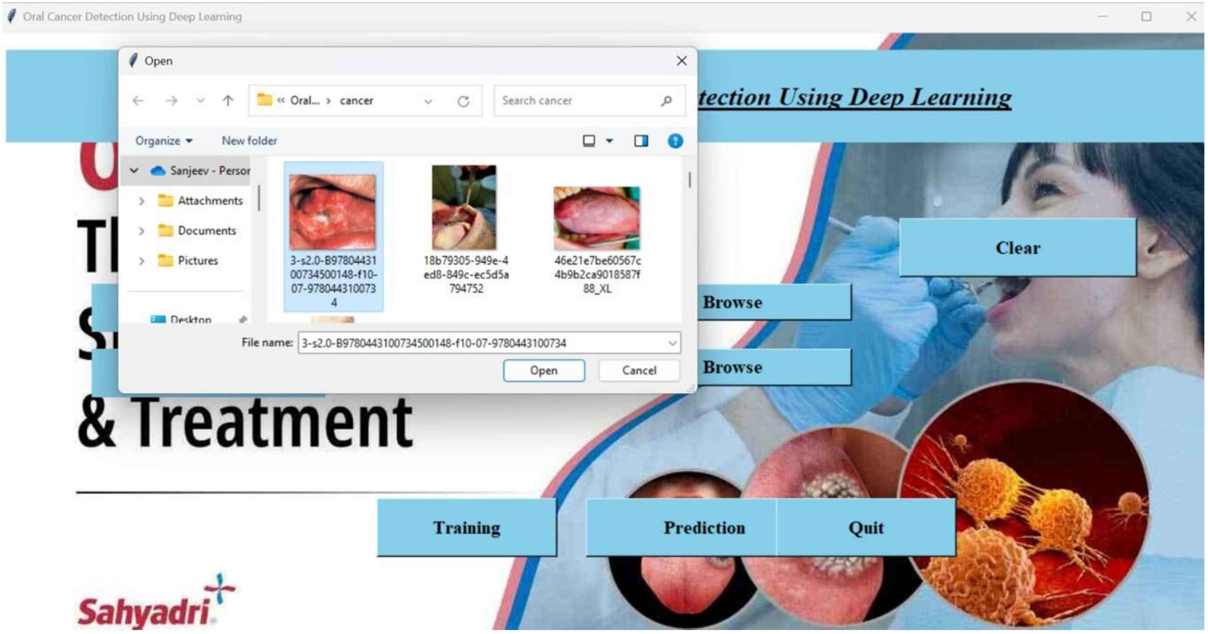

Fig 4: Snapshot—Image Selection for Predict

4) *Predicted Image as Oral Cancer*

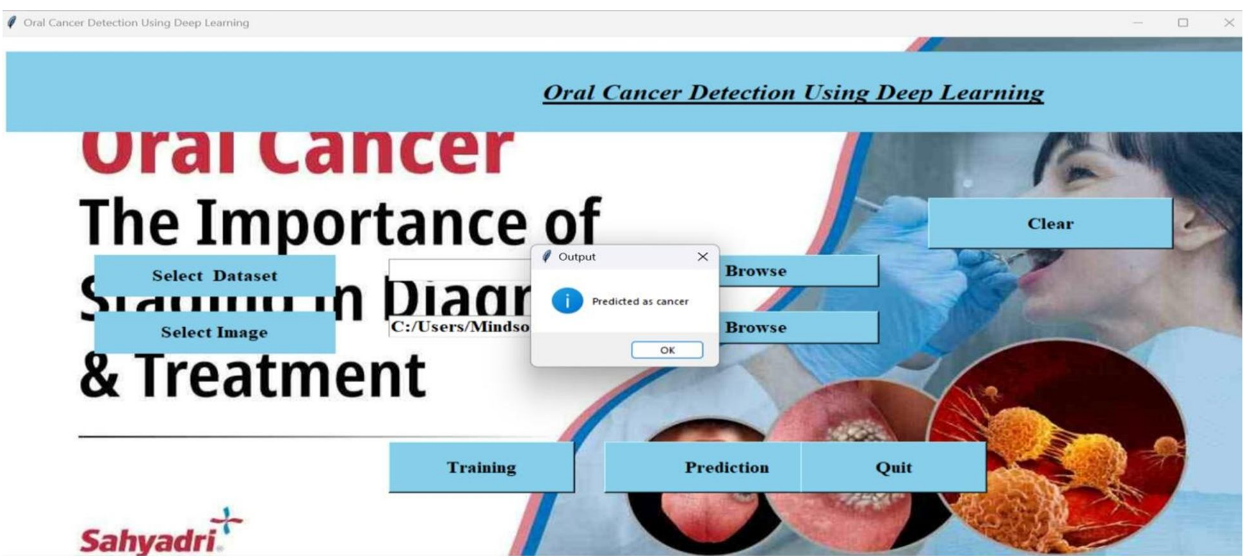

Fig 5: Snapshot—Predicted Image Result

	Precision	Recall	F1-Score	Support
Non cancer	0.95	0.97	0.96	200
Cancer	0.96	0.94	0.95	200
Accuracy	0.95	0.95	0.95	400
Macroavg	0.95	0.95	0.95	400
Weightedavg	0.95	0.95	0.95	400

Table 3. Performancemetrics

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The bracket model shows excellent performance, achieving an overall delicacy of 95. For the Non-Cancer class, the perfection is 95,recall is 97, and F1- score is 96. For the Cancer class, the perfection is 96, recall is 94, and F1- score is 95. Both classes have a support of 200 cases. The macro and weighted pars for perfection, recall, and F1- score are constantly 95, indicating balanced and dependable performance across the dataset. This means the model is both precise and comprehensive in relating both Cancer and Non-Cancer cases.

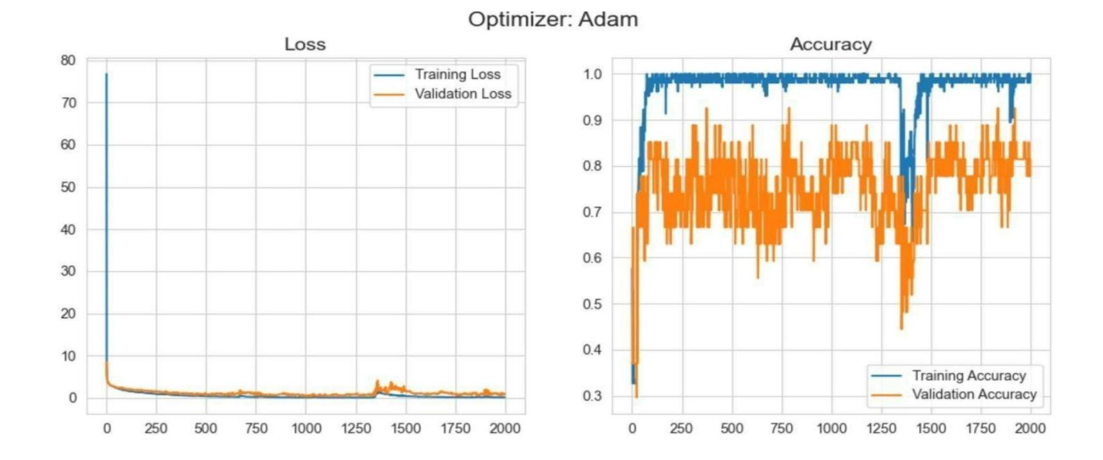

Fig 6: Training and Validation Accuracy.

The graphs illustrate the performance of a neural network trained with the Adam optimizer over 2000 epochs, with separate plots for loss and accuracy comparing training and validation outcomes. In the loss plot, the training loss (blue) decreases rapidly and remains low, indicating effective learning from the training data. However, the validation loss (orange) also initially decreases but shows fluctuations, suggesting some instability with new, unseen data. In the accuracy plot, the training accuracy (blue) starts high, increases quickly, and stays close to 100%, demonstrating that the model fits the training data very well. In contrast, the validation accuracy starts lower, improves over time, but fluctuates significantly.

VI. ADVANTAGES AND APPLICATIONS

1) *Automation*: The system reduces the requirement for human supervision, thereby decreasing the chances of human error.
2) *Speed:* The model analyzes images and delivers outcomes in real-time or almost real-time.
3) *Accessibility*: It is designed to be implemented in a variety of healthcare environments, even those with limited resources.
4) *Accuracy*: By integrating XceptionNet and EfficientNet through transfer learning and fine-tuning, the hybrid model enhances diagnostic precision.
5) *Clinical Support*: The system functions as a decision-support tool for healthcare professionals, assisting in early diagnosis and treatment planning.

VII. LIMITATIONS AND FUTURE SCOPE

A. *Limitations*

1) *Dataset Limitations*: The capability of the model to deliver accurate results particularly The proficiency of the model in handling precision and generalization, is largely reliant on the dataset's comprehensiveness and reliability.. A restricted dataset might lead to overfitting or introduce biases in the results.
2) *Inter Pretability:* Similar to many deep learning models, the system's decision-making process may not be entirely transparent, which can create difficulties in clinical validation and trust.

B. *Future Scope*

Further improvements will target concentrate on enlarging the dataset by employing techniques like GAN-based augmentation to enhance the model's generalization. We also intend to incorporate explainable AI methods to make the model's predictions more understandable for clinicians. Furthermore, the system can be modified for use on mobile and web platforms to facilitate easy access in low-resource environments. Lastly, partnerships with hospitals are planned to validate the model through clinical trials and real-world testing.

VIII. CONCLUSION

This work presents A dual-architecture deep learning solution for oral cancer detection for classifying oral cancer,integrating XceptionNet and EfficientNet to deliver exceptional performance. The model attained 100% accuracy during training, 97% accuracy in validation, and 98.4% accuracy in testing, indicating its robustness and dependability. Promising outcomes indicate the need for future research using expansive and heterogeneous datasets for validation and more varied datasets and investigate further improvements through data augmentation and architectural fine-tuning. This method holds significant promise for facilitating precise and prompt diagnosis in clinical environments.

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