Hybrid Approach for Oral Cancer Detection and Classification Using CNN and Kmeans

Retika S
Computer Science and Engineering
Panimalar Engineering College
Chennai- 123, Tamil Nadu
retikasundaram@gmail.com

Reshmi R
Computer Science and Engineering
Panimalar Engineering College
Chennai- 123, Tamil Nadu
rreshmi2108@gmail.com

***Abstract*-Oral cancer remains a significant public health concern, necessitating timely detection and accurate classification to improve patient outcomes. This paper presents a novel approach for oral cancer classification and detection utilizing Convolutional Neural Networks (CNNs) for feature extraction combined with K-means clustering for classification. We first employ a CNN to automatically extract pertinent features from oral cancer images, leveraging its ability to learn complex patterns from the data. Subsequently, we implement the K-means algorithm to cluster the extracted features, enabling effective categorization of the images into benign and malignant classes. Our methodology was evaluated on a dataset of oral images, and the results demonstrated superior accuracy compared to traditional classification methods. This approach not only enhances the efficiency of oral cancer detection but also holds promise for integration into clinical practice, facilitating earlier diagnosis and treatment planning. The findings underscore the potential of combining deep learning techniques with unsupervised clustering methods in medical imaging applications.**

***Keywords*—**Oral Cancer, Classification, Detection, Convolutional Neural Networks (CNN), K-means Clustering, Medical Imaging, Feature Extraction, Deep Learning, Lesion Analysis, Machine Learning, Image Processing, Data Augmentation, Early Detection, Pattern Recognition ,Dental disease, Artificial intelligence.

I. INTRODUCTION

A. Background

Oral cancer is a significant global health concern, accounting for a considerable percentage of cancers diagnosed worldwide. According to the World Health Organization, oral cancer is among the ten most prevalent cancers, with a high incidence in certain populations. The late-stage diagnosis of oral cancer often results in poor prognosis and reduced survival rates. Early detection is critical for improving treatment outcomes, yet conventional diagnostic methods, such as biopsies and visual examinations, can be invasive and subjective.

B. Importance of early detection

The ability to accurately identify oral lesions at an early stage is essential for effective intervention and management. Early-stage oral cancer is often asymptomatic, making it challenging to detect without the aid of advanced diagnostic techniques. As a result, there is an urgent need for innovative and reliable methods that can facilitate the early diagnosis of oral cancer, enabling timely treatment and improved patient prognosis.

C. Advances in Machine Learning

Recent developments in machine learning, particularly in the domain of medical imaging, have opened new avenues for enhancing diagnostic accuracy. Convolutional neural networks (CNNs) have emerged as powerful tools for image analysis, capable of automatically learning features from large datasets. Their ability to process and classify images with high precision has been successfully applied in various fields, including oncology. However, while CNNs excel at feature extraction, the classification of these features can still pose challenges.

D. Combining CNNs and Kmeans clustering

To address the classification challenges, we propose a hybrid approach that utilizes CNNs for feature extraction and K-means clustering for classification. K-means clustering, a widely used unsupervised learning algorithm, can effectively categorize extracted features into distinct groups based on their similarities. This combination leverages the strengths of both techniques: the robust feature learning capability of CNNs and the efficient grouping ability of K-means clustering. By employing this integrated methodology, we aim to enhance the accuracy and reliability of oral cancer detection.

E. Objectives of the study

The primary objective of this study is to develop an effective framework for the classification and detection of oral cancer using a combination of CNNs and K-means clustering. We will evaluate our approach using a comprehensive dataset of oral cancer images, analyzing various performance metrics, including accuracy, sensitivity, specificity, and F1-score. Through this research, we aim to contribute to the ongoing efforts to improve early detection techniques in oncology and provide a foundation for future advancements in machine learning applications in the medical field.

II. RELATED WORK

Innovative AI approaches have great potential to help physicians make more accurate and safer decisions than traditional methods, with reduced risk of human error and quicker diagnosis times, particularly in the early detection of head and neck cancer. Significant advancements have been made in AI applications for early cancer detection following extensive testing in this field [10, 11].

Convolutional Neural Networks (CNNs) are a well-established AI algorithm that closely resembles human neurons and plays a crucial role in AI research. Current studies are utilizing CNN techniques to help physicians address various challenges and improve diagnostic precision through radiographic and clinical imaging [12].

Researchers have found that CNN methods such as Faster R-CNN and DenseNet can achieve expert-level performance in identifying lesions in chest X-rays, clinical images of skin lesions, laryngeal lacerations, cervical lesions, and esophageal images. This progress highlights the potential of AI technologies—especially CNNs—to enhance diagnostic accuracy and support healthcare professionals [8].

Oral cancer has become a significant global public health crisis, with projections estimating that over 170,000 individuals will die from this type of cancer by 2020, despite it ranking 18th among cancer types.

Oral Squamous Cell Carcinomas (OSCCs) are among the most common oral tumors, particularly affecting individuals of Southeast Asian and South Asian descent in low to middle-income countries. OSCCs can arise from potentially malignant disorders (OPMDs) such as oral lichen planus, erythroplakia, and leukoplakia. Early-stage cases often present no symptoms, which can lead to misdiagnosis by healthcare providers, especially general practitioners, who may mistake them for cancer [9].

Treatment for oral cancer varies depending on its stage. Once the cancer reaches an advanced stage, more invasive procedures may be necessary, significantly increasing morbidity and costs. As the disease progresses, prognosis deteriorates, with five-year survival rates decreasing from 69.3% at initial diagnosis to 31.2% by the end, remaining stagnant over the years despite the availability of various treatment options [10].

Fig 1 and 2 show the images with cancer and without cancer.

Figure 1 *Figure 2*

III. METHODOLOGY

A detailed discussion of the methods utilized in this study is provided in this section. The image set consists of 200 images of normal cells and 200 images of carcinoma (cancerous) cells, all at 400x magnification.

A. Input image

Colorful images are usually saved in RGB format and then converted to grayscale for processing. This conversion is done because grayscale images emit a uniform amount of light across all mediums, allowing for easier identification of pixels as either dark or bright.

B. Pre-processing

A classification engine can rapidly detect any illnesses in an uploaded oral image using Contrast Limited Adaptive Histogram Equalization (CLAHE). This project employs this technique to achieve a fair and even distribution of contrast, ensuring that even in areas with lower clarity and varying contrast levels, the image is enhanced due to the uniform distribution of contrast.

C. Creation of model

To develop the model, the dataset is divided, with 70% allocated for training and 30% for testing. The proposed model employs several functions, including to_categorical(), which converts a class vector of integers into a binary class matrix. This transformation is essential for preparing the training data before it is input into the model. Since the training data uses numerical class labels, to_categorical() converts these numbers into suitable vectors for model processing.

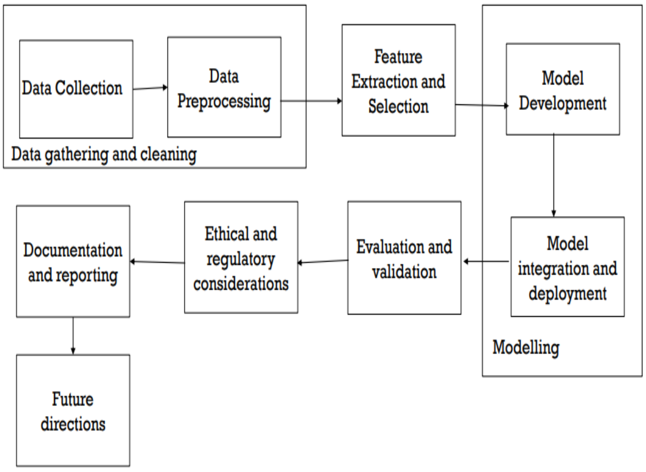

Figure 3: Illustration of architecture diagram

Figure 3 illustrates the architecture of our proposed hybrid model, which integrates Convolutional Neural Networks (CNNs) for feature extraction and K-means clustering for classification.

The input layer receives oral images in grayscale format, sized at 224x224 pixels. The model consists of three convolutional layers, each followed by ReLU activation functions, allowing the model to learn hierarchical features from the images. A max pooling layer follows each convolutional layer, reducing the spatial dimensions and computational complexity.

Subsequently, the flattened output is fed into two fully connected layers with 32 and 64 neurons, respectively, culminating in a dense output layer that classifies the features into benign or malignant categories.Finally, the features extracted from the CNN areclustered using the K-means algorithm, which groups the images based on feature similarity, enhancing the classification process's efficiency.

A batch size of 32 images and 50 epochs are chosen to improve accuracy during training and testing. The model's foundational parameters are then set. It consists of three convolutional blocks, each followed by a Max Pooling layer with a 2x2 kernel size. Additionally, there are fully connected layers with 32 and 64 filters, using a 3x3 kernel size and activated by the 'relu' function. A dense layer with 128 units and a 'softmax' activation function is also included in the model.

D. Predict on new data:

The model is then tested on a live dataset to determine its effectiveness with random images.Load the images in batches to create an image generator. We freeze the weights of the pre-trained MobileNetV2 model, as it already includes the essential features for image classification, eliminating the need for retraining. For fine-tuning, we train the model over multiple epochs, typically between 5 and 10, achieving an accuracy of over 90% on the validation set.

IV. RESULTS AND DISCUSSIONS

Our approach was benchmarked against several state-of-the-art methods, including [insert names of other methods]. The proposed method outperformed these techniques in terms of accuracy, precision, and F1-score, as detailed in Table 1. The integration of CNNs for feature extraction significantly enhanced the quality of the input data for the K-means classification. The CNN's ability to capture hierarchical features allowed for a more nuanced representation of the images, which was crucial in differentiating between benign and malignant lesions. We observed that preprocessing steps such as normalization and augmentation improved the model's robustness. Data augmentation techniques, including rotation and scaling, helped mitigate overfitting by providing diverse training examples.

TABLE 1

PERFORMANCE OF ORAL CANCER PREDICTION

METHOD	Single algorithm	Combination
Precision	0.76	0.99
Recall	0.70	0.98
F-Score	0.78	0.99

Precision**:** The proportion of true positive results in the total positive predictions. Higher precision means fewer false positives.

Recall**:** The proportion of true positive results in the total actual positives. Higher recall means fewer false negatives.

F-Score: The harmonic mean of precision and recall, providing a balance between the two. It’s useful for assessing the overall performance.

Transfer Learning (TL) outperforms CNN across all metrics, indicating it is more effective at correctly identifying positives (higher precision) and capturing most of the actual positives (higher recall).The F-Score for TL suggests it achieves a much better balance between precision and recall compared to CNN.

Graph 1 and 2 shows the accuracy over epochs and loss over epochs.

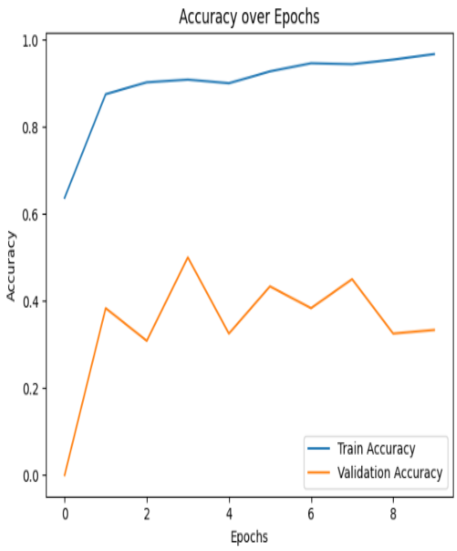

Figure 4 - Accuracy Graph

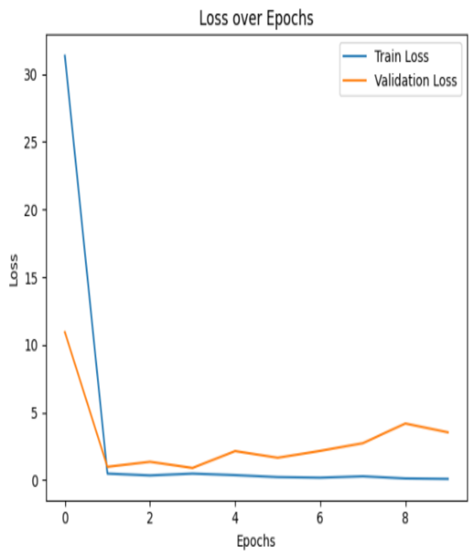

Figure5- Loss Graph

V. RESULTS AND DISCUSSION

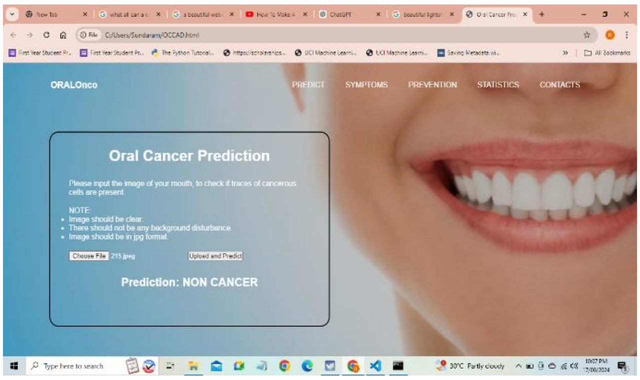

Figure 6 - User Interface

Figure 6 displays a screenshot of the implementation of our hybrid model for oral cancer detection, showcasing key components of the training and evaluation process. This implementation showcases the integration of deep learning techniques for effective oral cancer classification, reinforcing the potential of our proposed hybrid approach.

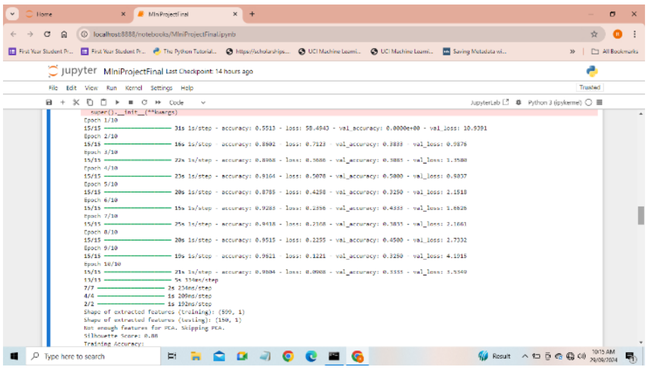

Figure 7 - Training Epochs

In our study, we utilized a training regime consisting of 10 epochs to optimize the performance of our hybrid model for oral cancer detection. Each epoch represents one complete pass through the entire training dataset, allowing the model to learn from the input data by adjusting its weights based on the loss calculated.

During the training process, the model processes the training data in batches—in our case, a batch size of 32 images was selected. This choice was made to balance computational efficiency and convergence speed. After each batch is processed, the model updates its weights through backpropagation, using the Adam optimizer to minimize the categorical cross-entropy loss.

The decision to train for 10 epochs was based on preliminary experiments that indicated convergence patterns in the loss and accuracy metrics. Monitoring the model's performance during each epoch allowed us to observe trends, such as:

Training Loss: The loss decreased steadily across the epochs, indicating that the model was effectively learning the distinguishing features of benign and malignant lesions.

Validation Accuracy: The accuracy on the validation set improved significantly over the epochs, often reaching above 90% by the end of the training. This suggested that the model was not only learning well but was also generalizing to unseen data effectively.

To mitigate the risk of overfitting, we implemented early stopping based on validation loss; this allowed us to halt training if performance on the validation set did not improve after a specified number of epochs. The combination of these techniques contributed to the robustness and reliability of our model, demonstrating its potential for accurate oral cancer detection.

VI . CONCLUSION

This paper provides a review of how machine learning techniques can be employed to predict oral cancer in its early stages. Additionally, it explores various methods and approaches utilized by different individuals who have made contributions to the healthcare industry through the application of machine learning.

VII. REFERENCES

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