

An Integrated CT Image Approach for Oral Cancer Analysis using DOAKC Segmentation and ORB Feature Extraction

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ABSTRACT

Oral cancer remains a main health concern, often diagnosed at sophisticated periods, leading to poor patient outcomes. Early detection using medical imaging significantly improves survival rates. Manual understanding of CT images is prolonged and prone to error, contributing to delayed diagnosis. Current diagnostic tools lack automation and accuracy in early-stage cancer detection. This research proposes a Probabilistic Ant Optimized Decision Tree Classifier (PAODTC) model that processes CT images for early-stage oral cancer detection. The dataset for this research is sourced from the Cancer Imaging Archive (TCIA), an open-access cancer image repository. CT images were resized for uniformity in pre-processing. Dynamic Optimal Adaptive K-Means Clustering is employed to effectively segment the cancerous regions within the images, allowing for precise delineation of affected tissues and enhancing the accuracy of extracting features. Next, the Oriented FAST and Rotated BRIEF (ORB) algorithm retrieved essential characteristics from the segmented images, enabling a robust representation of the vital characteristics necessary for effective analysis. Data augmentation techniques, including adding Gaussian noise, were applied to enhance data diversity. Classification utilizes the proposed PAODTC model, which integrates AdaBoost, Decision Tree, and a modified Ant Colony Optimization for classification. This Python model, which was created and put into use, successfully distinguishes between malignant and non-cancerous tissues using the features that were retrieved. The results established that the K-means clustering model significantly improved the performance in terms of segmentation dice score (0.9288), average precision (0.9366), and evaluation time (0.0938). PAODTC significantly outperforms existing approaches in accuracy and detection efficiency.

Keywords: Oral Cancer, Resize, Dynamic Optimal Adaptive K-Means Clustering, Oriented FAST and Rotated BRIEF (ORB), Data Augmentation

INTRODUCTION

Oral cancer is a kind of head and neck cancer that originates in the tissues of the mouth or throat. If detected early, oral cancer is highly treatable and often curable. Early-stage oral cancer refers to tumours that are localized and have not spread to another part of the body, making them easier to treat [1]. The simplicity of inspecting the mouth for abnormalities allows for the early detection of oral cancer by healthcare professionals or dentists. This early detection significantly raises the probability of successful treatment and improvement.

The Anatomy of the Oral Cavity and Its Importance

The oral cavity, or mouth, comprises various important structures such as the lips, gums, tongue, cheeks, and the floor and roof of the mouth [2]. Each of these parts plays a vital role in functions like speaking, chewing, swallowing, and maintaining oral health. The lips and tongue are especially important for speech and swallowing, while the gums help to protect and.

support the teeth. Oral cancers primarily affect the lining of these areas, specifically the squamous cells. They result in difficulties in chewing, speaking, and swallowing if left untreated [3]

Early detection in these areas is crucial to preventing further complications. Mouth cancer originates in various areas of the mouth, incorporating the lips, tongue, gums, cheeks, hard palate, and behind wisdom teeth. Nine out of ten mouth cancers are Squamous Cell Carcinoma (SCC) that develops in the flat, skin-like cells lining the inside of the mouth. **Figure 1** denotes the representation of Anatomy of the Oral cancer.

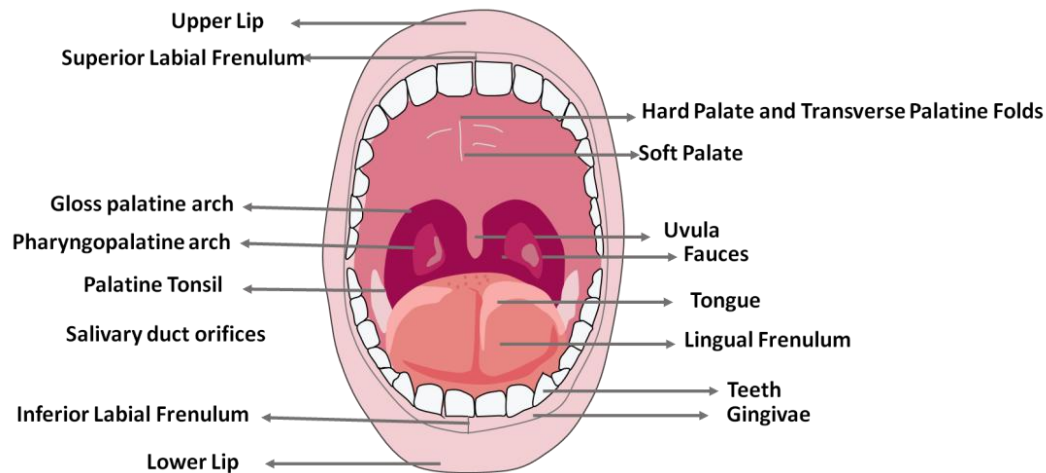


Figure 1: Oral cancer Anatomy

Types of Early-Stage Oral Cancer

Oral cancer encompasses a variety of tumour types, but the most prevalent is SCC accounts for more than 90% of oral cancer cases. SCC arises in the SC are flat, scale-like cells that line the oral cavity. These cells are responsible for the mucosal lining of the mouth and throat, and when cancer forms in these cells, it spreads to nearby tissues [4]. Early-stage SCC typically presents as small, localized lesions that appear as constant sores or patches in the mouth that do not cure. The tumor grows slowly but also infiltrates deeper into surrounding tissues if left untreated, affecting functions such as chewing, swallowing, and speaking [5]. In addition to SCC, there are several less common types of oral cancer, including salivary gland tumors and lymphoma. These cancers arise from different tissues in the mouth:

- **Salivary Gland Tumors:** Salivary gland cancers, including adeno carcinoma and adenoid cystic carcinoma, are rare but affect the mouth and throat, particularly the major salivary glands [6]. Adeno carcinomas form in the ducts and cause swelling or masses in the mouth or jaw area.
- **Lymphoma:** Lymphomas, including non-Hodgkin's lymphoma, affect the oral cavity or throat, often presenting as swelling or lumps in oral tissues [7]. Originating from the immune system's lymphatic system, early identification and action are critical for successfully managing this uncommon form of oral cancer.

Another important kind of oral cancer is verrucous carcinoma. It is an unusual vice-type of SCC. This type is considered low-grade and slow-growing, meaning it typically does not spread to distant parts of the body. Verrucous carcinoma is characterized by its warty, cauliflower-like appearance and is generally less aggressive than other forms of oral cancer [8]. Despite its slower progression, verrucous carcinoma still invades surrounding tissues and impacts the function of the mouth, such as chewing and speaking. Early-stage verrucous carcinoma is typically localized, and when treated early, the prognosis is favorable. However, it becomes more invasive over time if not properly managed. While SCC remains the most prevalent, all types of oral cancer, whether common or rare, require prompt diagnosis and treatment [9]. Early intervention is crucial for minimizing the impact on daily life functions, preserving quality of life, and preventing the spread of cancer to other areas [10]. Regular dental checkups and self-examinations of the mouth help in the premature recognition of oral cancer, leading to more successful treatment results. Figure 2 denotes the Symptoms of Oral cancer.

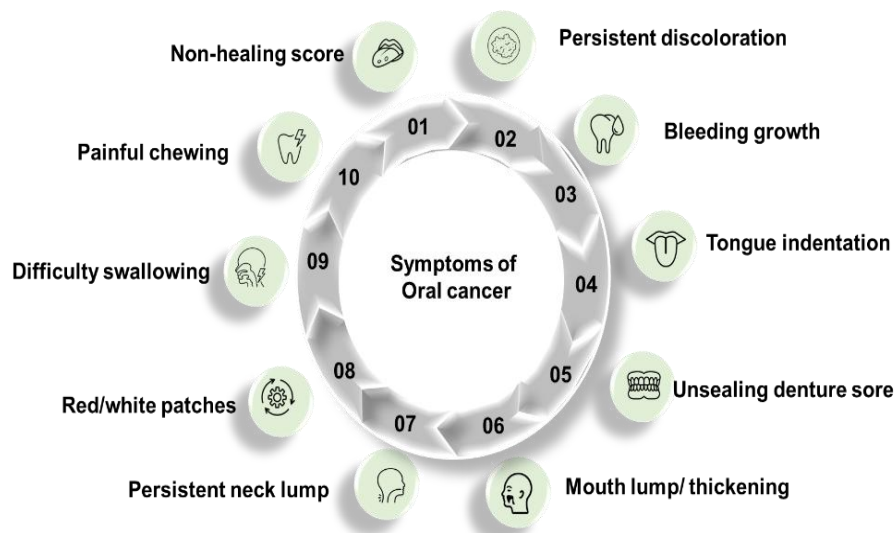


Figure 2: Symptoms of Oral cancer

LITERATURE REVIEW

An improved Convolutional Neural Network (CNN) for the early recognition of oral cancer by combining the Seagull Optimization Algorithm (CSOA) and Particle Swarm Optimization (PSO) to enhance CNN architecture and training [11]. The research [12] aimed to develop an AI model using a portable electronic oral endoscope to identify oral cancer using intraoral images. The U-shaped CNN (U-Net) and Residual Neural Network (ResNet)-34 DL models were used. The validation phase showed higher loss and Dice values, but further improvement is needed for practical clinical application. The model's accuracy and precision were expected to improve with further development. To improve oral cancer detection by applying advanced digital processing technologies, including wavelet features, Bag Histogram of Directed Gradients (BHOG), and fuzzy optimization, to identify and categorized cancer cells [13]. The CNN classifier based on regions was employed for classification. An updated system of the Northern Goshawk Optimization (NGO) method was used to optimize Gated Recurrent Unit (GRU) networks. The research [14] investigated an innovative method to oral cancer diagnosis. Benefits of the method include early identification of oral cancer, excellent accuracy, and the capacity to examine sizable and intricate datasets. Oral SCC (OSCC) is a malignancy that disrupts the development of layers and membranes in surrounding tissues [15]. DL has enabled early diagnosis of OSCC through computerized early diagnosis of oral histopathological images. The research used a CNN model, Inception-Resnet-V2, to classify the histopathological images. The modified model used a repository of oral cancer histopathology images, outperformed the original model with an accuracy of 91.78%, representing the possible of DL in biomedical image classification. An automated system for early detection and screening of SCC tongue morbidity and death [16]. The proposed model, the Optimal Archimedes Shooty Tern Deep Network (OASTDN), improved the identification and detection of oral cancer. The model used a hybrid Archimedes Optimization Algorithm (AOA) and Shooty Tern Optimization (STO) method to tune the influence of the Deep Belief Network (DBN). The employ of DL in diagnosing and predicting oral cancer prognosis using CNNs and Recurrent Neural Networks (RNNs) was explored [17]. It emphasized the significance of oral cancer databases in research and medical procedures. The research [18] presented an automated architecture for early diagnosis of OSCC using Self-Attention CNN and residual network information fusion and optimization. Hyper-parameters were initialized with the Whale Optimization Algorithm (WOA), factors were fused using canonical correlation analysis, and final factors were classified utilizing neural networks.

METHODOLOGY

The research employs a novel framework for automated early-stage oral cancer diagnosis by processing CT images using advanced image pre-processing techniques. The research gathers CT imaging dataset from TCIA, after which the images were resized to maximize computing efficiency for ML models and ensure homogeneity. Advanced segmentation is used to improve segmentation accuracy, feature resilience, and noise reduction. Dynamic Optimal Adaptive K-Means, ORB-based feature extraction, and Gaussian Filter-based data augmentation are used. Figure 3 demonstrates the research outline.

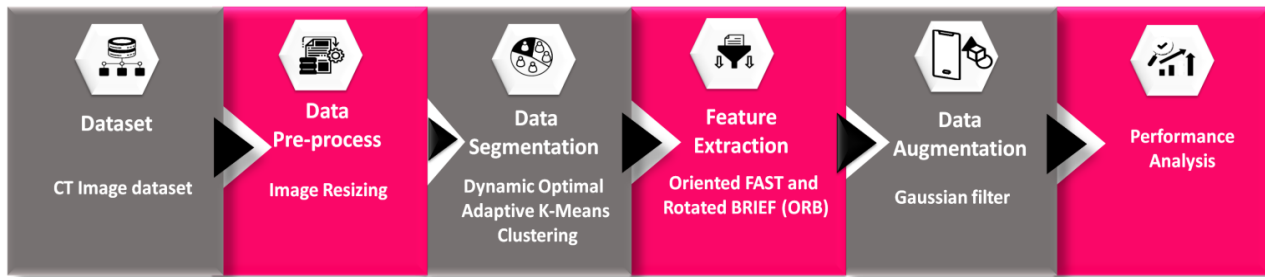


Figure 3: Research outline

Data collection

The research gathered a comprehensive CT imaging dataset from [20]. The CancerImaging Archive (TCIA) provides publicly available medical images for cancer research. This dataset includes high-resolution CT scans from various cancer types, annotated with key clinical information to support diagnostic and therapeutic studies. The collection aims to facilitate advanced ML applications for early cancer detection and treatment planning.

Data Pre-processing using image resize

Image resizing is an essential step in data preparation, ensuring that all images in a dataset conform to a uniform dimension, which is crucial for consistent input into ML models. Reducing the variation in image dimensions enhances model performance and optimizes computational efficiency when images are resized to a standard size. It also ensures that feature extraction methods operate consistently across all images and helps to avoid over fitting. The process involves loading images from a specified input directory, resizing each image to 224x224 pixels, and saving the resized images into a new output directory. During this procedure, a visual comparison is generated, displaying both the original and resized images for the last processed sample. This ensures quality control and allows for quick verification of the resizing operation.

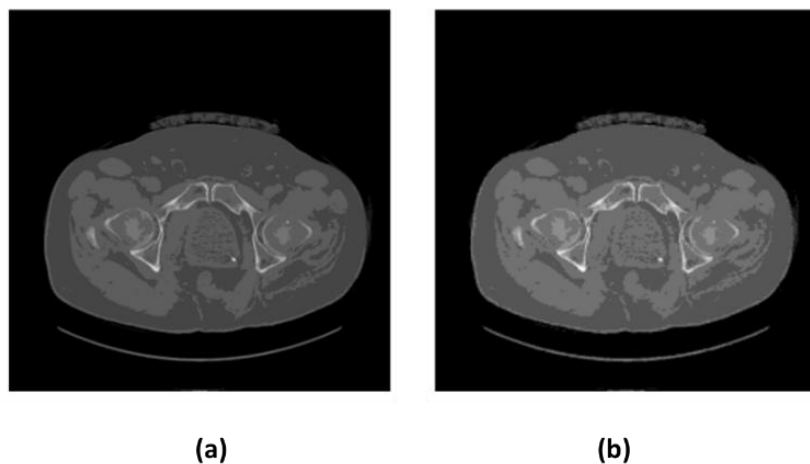


Figure 4: Outcomes of (a) Before and (b) after resizing the image

After processing, the final resized images are displayed side by side using Matplotlib. Each image is shown with its title and without axis labels for simplicity. **Figure 4** shows the images are uniformly scaled to 224x224 pixels, ensuring consistency and essential content, and the output directory contains all resized images for further processing or model training.

Segmentation using Dynamic Optimal Adaptive K-Mean Clustering

The concept of Dynamic Optimal Adaptive K-Means Clustering builds upon the standard K-Means clustering algorithm by incorporating adaptive and dynamic elements that enhance the clustering performance, particularly in applications such as medical image segmentation (cancer). K-Means Dynamic Optimal Adaptive precisely delineates the afflicted tissues and improves the accuracy of feature extraction, clustering is utilized to efficiently partition the malignant spots within the images. The k-means approach gives each cluster a k-centroid to spread them out as widely as possible and average the data in a collection with the centroid next to it. The clusters' bary centre's are calculated as l new centroids once all remaining points have been located. The l centroids move repeatedly until there are no more changes after a fresh binding among the identical data indicates and the closest new centroid. K-means aims to minimize the purpose function known as the squared-error role.

$$I = \sum_{i=1}^w \sum_{j=1}^l ||w_j^i - D_i||^2 \quad (1)$$

$||w_j^i - D_i||^2$ is the distance among a data and the cluster center. This is a sign of the separation between each cluster center and the total number of points of data. Equation 1 demonstrates how to use the k-means clustering technique to separate images into sections.

Initialization phase: A k-means image clustering process is utilized for a finite number of rounds, and an integrity role is generated. This stage marks the initial round of the suggested adaptive segmentation technique.

Adaptive segmentation phase: Image clustering segmentation is carried out. Beginning with the final iteration in the initialization phase, K-means clustering is employed for an innovative m integer of iterations m ($m = 10$ iterations). The feature-based computation, feature-based assessment, new center creation, and object selection are some of the sub processes that constitute this process.

Initialization phase

In the section, these two stages are thoroughly explained, along with the procedures and feature attributes unique to each stage. The adaptive segmentation approach's initialization stage uses k-means clustering for m rounds. The first new clusters are formed by distributing new centres. This iteration marks the first calculation of goodness. The integrity task is definite as the mean circularity of all subsequent items. The circularity proportion is the region of a form separated by the region of a round with the identical perimeter. It is articulated accurately as follows in Equation 2:

$$fcirc = \frac{4 * \pi * B}{O^2} \quad (2)$$

Where O and B stand for the object's area and perimeter, respectively. For a circle, the $fcirc$ function is equal to one, whereas, for all other shapes, it is less than one. The sum of pixels in every divided cluster is used to calculate the area. Equation 3 is used to determine the goodness function.

$$GOODNESS = \frac{\sum_{j=1}^N fcirc_j * B_j}{\sum_{j=1}^N B_j} \quad (3)$$

Where B_j represents the j^{th} object's area and $fcirc_j$ represents its circularity ratio. To increase the rates of huge things and decrease the rates of little things, the object's circularity ratio is multiplied by its area. The core of the suggested approach is the adaptive segmentation point. Beginning with the last iteration, the k-means method is used for an additional m iteration in this phase. Equation 3 is used to compute goodness utilizing the feature-based computation approach. The feature-based assessment approach is then used to evaluate the current goodness with that of the previous iteration. If the present integrity is greater, or if the innovative integrity rate is smaller than the old rate, the present condition is preserved and the previous outcomes are removed. When the present integrity is inferior, the new center's invention technique is utilized to build novel clusters from the brightest two groups. Until M algorithm iterations are reached or the goodness result stays the same, these procedures are repeated. Lastly, the most circular objects are chosen using the object selection procedure.

Dynamic Color Mapping:

The algorithm employs dynamic random colors for visualizing the segmented clusters. This dynamic aspect ensures that each clustering run represents different regions distinctly, improving the interpretability of the results. By assigning random colors to clusters, the algorithm provides a unique visualization for each execution, allowing for better differentiation between segments in an image. The original grayscale image and the segmented image are compared with regions highlighted in random colors (Figure 5).

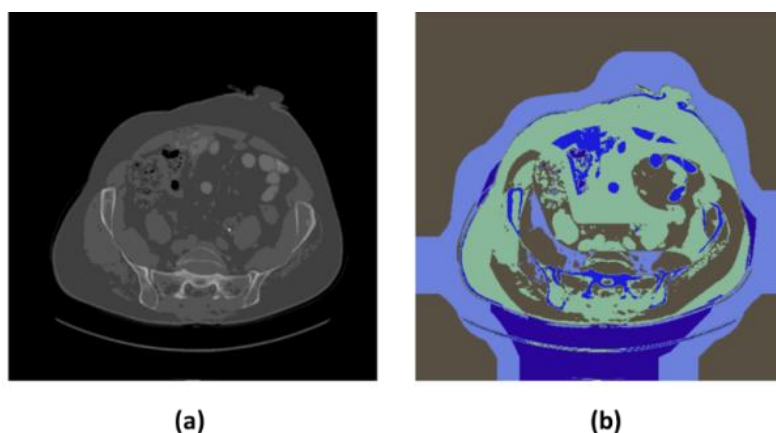


Figure 5: Outcomes of (a) the Original grayscale image and (b) the colored segmented image

K-means clustering is applied to the pixel values with a specified number of clusters ($k=5$ in this case) as represented in Figure 6. It denotes the results of K-means clustering are presented with particular attention to (a) clusters 1, (b) 2, (c) 3, (d) 4, and (e) 5.

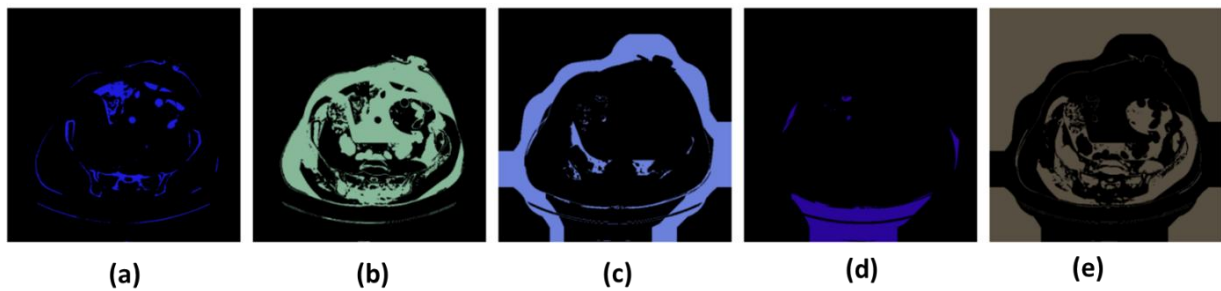


Figure 6: Outcomes of K-means clustering ((a) cluster 1, (b) cluster 2, (c) cluster 3, (d) cluster 4, (e) and cluster 5)

The adaptive k-means clustering technique enhances medical image segmentation by improving accuracy in delineating afflicted tissues, with a focus on feature extraction and object selection for more precise outcomes.

Feature Extraction using Oriented FAST and Rotated BRIEF (ORB)

The purpose of this research is to handle a collection of images from selected input data by extracting image descriptors using the ORB feature identification technique. The ORB method is a feature extraction technique that utilizes features from LONG descriptors and FAST keypoint detectors. It improves concert by incorporating the potency and density of BRIEF descriptors with the effectiveness of FAST keypoint detectors. This system detains more significant and diverse character, rising its strength and efficiency in functions like image recognition and object detection. The ORF system is calculated to detain more diverse features in Equation 4.

$$n_{or} = \sum_{w,z} w^o z^r J(w, z) \quad (4)$$

Where n_{or} denotes an image's $(o + r)^{th}$ order moment and the intensity $J(w, z)$ varies according to an image coordinate. The centroid is reached by taking into account the moments in Equation 5.

$$D\left(\frac{n_{10}}{n_{00}}, \frac{n_{01}}{n_{00}}\right) \quad (5)$$

After a vector is created from the center to the centroid $\overrightarrow{OD}$, the patch's orientation becomes as follows: $\frac{n_{10}}{n_{00}}, \frac{n_{01}}{n_{00}}$ where stands for the arctan quadrant-aware variant. Regardless of the nature or shape of the corner, the angle measurement stays constant, making the impact of the lighting variable at corners insignificant. It is crucial to compute the moment with respect to the w and z coordinates inside a circular zone of radius q to improve rotational invariance.

By choosing an ideal patch size of q , the w and z coordinates are ensured to fall between $[-q, q]$. Usually, instability results from the value of $|d|$ being 0 when the Hessian measure is applied. The FAST method, which greatly improves system efficiency, does not have this problem. For obtaining rotational invariance in a variety of applications, FAST is a better option than the Hessian measure due to the stability and efficiency gains it offers. A rotation-aware module called q-BRIEF, a more sophisticated form of the steered BRIEF descriptor, is incorporated into the ORB algorithm. This enhancement is coupled with a suitable learning phase designed to identify fewer correlated binary characteristics. To enhance the traditional BRIEF process, an orientation module is incorporated into ORB on the presumption that a smooth image patch exists (Equation 6).

$$\theta = \text{atan2}(n_{01}, n_{10}) \quad (6)$$

Equation 7 illustrates how the feature is processed after taking into account the patch, which is thereafter expressed as a vector of mbinary tests as shown below. In this case, $o(w)$ represents the patch's intensity at a specific position w .

$$s(o; w, z) := \begin{cases} 1; & o(w) < o(z) \\ 0; & o(w) \geq o(z) \end{cases} \quad (7)$$

A Gaussian distribution is applied close to the patch's center, and the vector length mis chosen at 256 to provide modest results. Steered BRIEF is the first stage of this technique, which involves employing key point orientation to guide BRIEF. This is accomplished by using the key point orientation to guide the BRIEF description for a feature set that has m binary tests at certain locations. Better accuracy and robustness in feature representation are therefore ensured. The following provides a matrix Equation 8 represents the binary test at a certain position w :

$$e_m(o) = \sum_{1 \leq j \leq m} 2^{j-1} \tau(o; w_j, z_j) \quad (8)$$

A steered version of T is then obtained by using (patch orientation) and (equivalent rotation matrix) as follows in Equation 9:

$$T = \begin{pmatrix} w_1, \dots, w_m \\ z_1, \dots, z_m \end{pmatrix} \quad (9)$$

Therefore, the steered BRIEF function is given by Equation 10:

$$T_\theta = Q_\theta T \quad (10)$$

The angle is discretized in twelve-degree increments, and a lookup table of previously calculated BRIEF patterns is created. Accurate BRIEF descriptor calculation is possible with precise points, maintaining key point orientation across perspectives, and enhancing feature representation reliability and accuracy. Figure 7 illustrates the outcomes of (a) original image and (b) extracted image

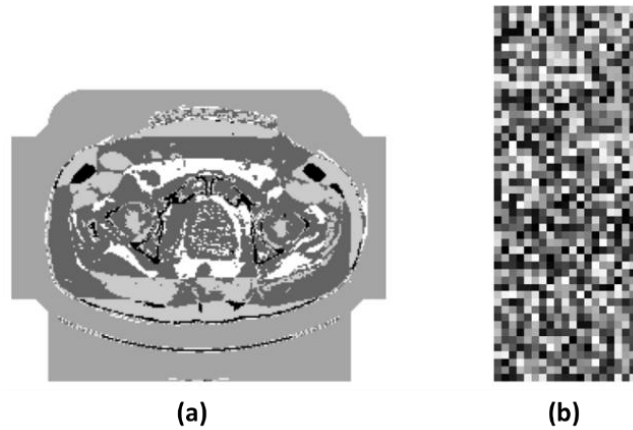


Figure 7: Outcomes of (a) original image and (b) extracted image

ORB captures distinctive features through FAST key point detectors and BRIEF descriptors, enhancing image recognition by focusing on relevant and stable features.

Data Augmentation using Gaussian Filter.

Following feature extraction, Data augmentation using a Gaussian filter (GF) helps enhance the variability of oral cancer images by smoothing and reducing noise, improving model generalization. It also aids in creating more diverse training data, which enhances the robustness of ML models in detecting oral cancer. The GFs are used to examine the images. In the oral cancer image dataset, the GF technique is employed to reduce noise while producing better and more precise quality. Oral cancer images are susceptible to noise during processing, affecting their efficiency in analysis and diagnosis. This system uses GFs for image smoothing and noise removal, employing a custom kernel for convolutional operations and Gaussian distribution values for professional appearance (Equation 11).

$$S(y) = \frac{1}{\sqrt{2\pi\sigma^2}} a^{\frac{(y-\mu)^2}{2\sigma^2}} \quad (11)$$

In the above instance, $S(y)$ is the value of the function at position y , which denotes the input value, such as the pixel position in an oral cancer image. μ is the mean of the distribution, determining the center of the Gaussian curve, while σ is the SD, controlling the width or spread of the curve. The constants π and e are mathematical constants. Gaussian filters are applied to oral cancer images to reduce noise and enhance image excellence, thereby augmenting the dataset and enhancing the model's robustness for better generalization.

PERFORMANCE ANALYSIS

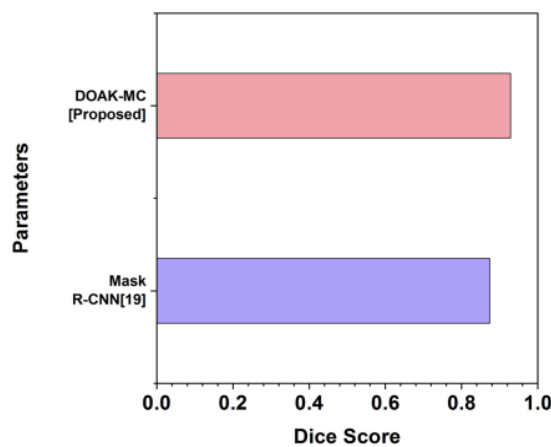
The DOAK-MC model is evaluated for early-stage oral cancer diagnosis using Python 3.8. The suggested segmentation method is evaluated using metrics like accuracy, evaluation time, average precision, and dice score. To evaluate the DOAK-MC model's ability to segment malignant tissues, it is compared to Mask Region-based Convolutional Neural Network (Mask R-CNN) [19]. Table 1 shows the determination of existing and proposed method outcomes.

Table 1: Outcomes of Existing and Proposed Segmented Result

Parameters	Mask R-CNN[19]	Dynamic Optimal Adaptive K-Mean Clustering(DOAK-MC)
Dice Score	0.874	0.9288
Average precision (AP) (IoU=0.75)	0.826	0.9366
Evaluation Time (seconds)	0.332	0.0938

Dice score

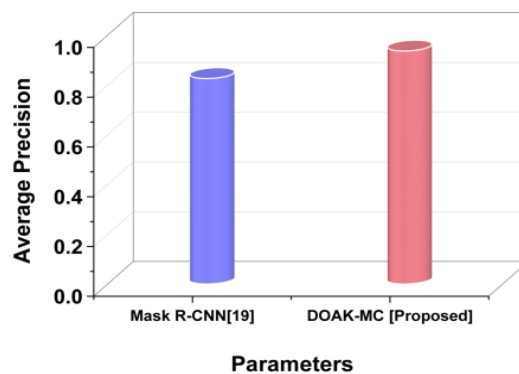
Dice score is utilized to assess the resemblance connecting predicted and ground truth segmentations in image analysis tasks, with values ranging from 0 to 1. The dice score compares the cancerous regions identified by the algorithm with the ground truth, indicating how accurately the algorithm delineates affected tissues. Figure 8 demonstrates the analysis of the dice score.

**Figure 8:Evaluation of dice score**

With a superior Dice Score of the DOAK-MC (0.9288) achieves superior than Mask R-CNN (0.874) in the segmentation of malignant regions. DOAK-MC is a capablesystem for medical image analysis since it demonstrates enhanced accuracy in important afflicted tissues and improves the overall efficiency of early-stage oral cancer recognition.

Average precision

Precision quantifies the proportion of projected positive cases that are true. The model's accuracy in segmenting malignant tissues is evaluated with an emphasis on reducing false positives. It is less probable that non-cancerous tissues are mistakenly identified as cancerous when accuracy is high. Figure 9 represents the average precision rate.

**Figure 9:Estimation of Precision rate**

The DOAK-MC approach achieves a score of 0.9366 as opposed to, outperforming Mask R-CNN (0.826) in terms of Average Precision (AP) with an IoU of 0.75. This indicates that DOAK-MC helps to segment the oral cancer in its early stages by offering a more accurate and exact segmenting of malignant tissues

Evaluation time

It quantifies how long it takes a model to analyze and forecast data. The effectiveness of the DOAK-MC and PAODTC models in categorizing CT scans for the early recognition of oral cancer is evaluated by the trade-off between speed and accuracy. Figure 10 shows the evaluation time.

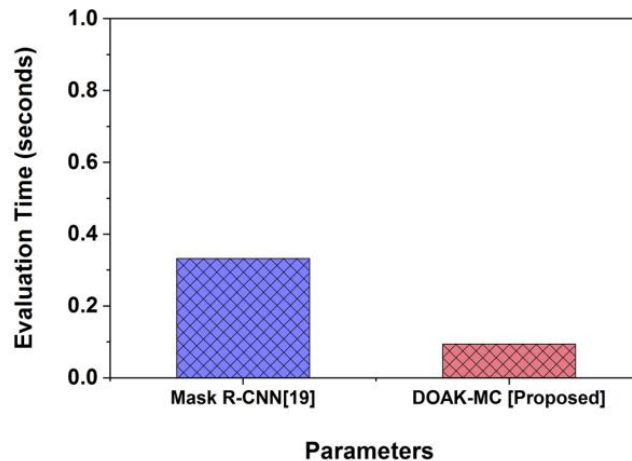


Figure 10: Determination of evaluation time

In terms of evaluation time, the DOAK-MC approach performs noticeably better than Mask R-CNN, taking only 0.0938 seconds as opposed to 0.332 seconds. This indicates that DOAK-MC is a viable option for real-time cancer segmentation applications since it is not only more effective but also appropriate for quicker processing.

Accuracy

A segmentation model's accuracy is determined by counting the number of correct predictions. This evaluates the PAODTC model's ability to distinguish between malignant and non-cancerous tissues. High accuracy denotes dependable tissue categorization and efficient early-stage oral cancer detection. Figure 11 displays the estimation of accuracy.

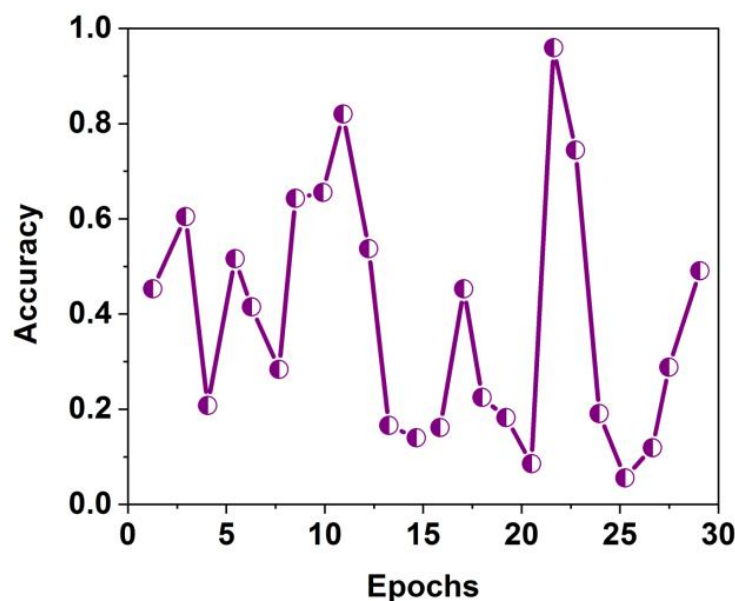


Figure 11: Assessment of accuracy

The outcome highlights variations in accuracy across many epochs by displaying the variation in accuracy for the DOAK-MC model. Around the epoch, the accuracy peaks and then noticeably declines. According to this pattern, the model's performance either stabilizes or becomes unstable during training, suggesting that more tuning or changes are required to increase consistency in subsequent epochs.

DISCUSSION

By combining Dynamic Optimal K-means clustering for segmentation is compared with Mask R-CNN [19]. This performed well on segmentation functions but has limited generalization and high computing difficulty. Mask R-CNN [19] was less fitting for early-phase recognition, particularly in excessive datasets, since its dependence on substantial manual tuning and challenges in tackling restrained, small malignant patches. By lowering computational requirements, using data augmentation techniques like Gaussian noise to improve generalization, and automating feature selection and categorization, K-means clustering overcomes these drawbacks and provided a scalable, efficient, and more precise technique for early-stage oral cancer detection. As findings, it was a capable device for concurrent clinical applications.

CONCLUSION

CT image processing is important for early-stage oral cancer identification because it has the potential to improve patient outcomes and diagnosis accuracy. The research was to create a PAODTC system to enhance and mechanized the recognition process. The results established that the K-means clustering model significantly improved the performance in terms of segmentation dice score (0.9288), average precision (0.9366), and evaluation time (0.0938). A single dataset and the prospect of noise in real medical situations were two drawbacks, although the method's notable outcomes. Successive research endeavours focused on enlarge the dataset to improving the system by integrated extra variables and estimating the methodology in other clinical settings to advance validated its flexibility and suitability.

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