Segmentation and Classification of Oral cancer

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*Abstract*— This study presents an investigation into the development of a Oral cancer represents a significant global health challenge due to its increasing incidence and often late-stage diagnosis. Early detection and precise diagnosis are crucial for improving patient outcomes. This study investigates advanced methodologies for the segmentation and classification of oral cancer using medical imaging techniques. We propose a novel framework that integrates deep learning algorithms with traditional image processing methods to enhance the accuracy and efficiency of oral cancer detection. The segmentation component employs convolutional neural networks (CNNs) to delineate cancerous regions from surrounding tissues in oral cavity images. Following segmentation, a classification model leverages feature extraction to categorize the lesions into various stages and types of oral cancer. Our approach is evaluated using a diverse dataset of oral cavity images, demonstrating improved performance over conventional methods in terms of accuracy, sensitivity, and specificity. This integrated framework offers a promising tool for clinicians, potentially leading to earlier detection and more personalized treatment strategies for oral cancer patients.

Keywords— Oral cancer, Classification Model, Convolution neural network.

# Introduction

﻿Oral most cancers, which incorporates cancers affecting the lips, tongue, cheeks, ground of the mouth, and difficult palate, presents a significant worldwide health mission. It is one of the ten maximum commonplace cancers global and is in particular regarding due to its high costs of both morbidity and mortality. This difficulty is specially excessive in areas like South Asia and components of Africa, in which tobacco use and negative oral hygiene are massive. According to the World Health Organization (WHO), over 377,000 new cases of oral most cancers are diagnosed each yr. Sadly, the five-12 months survival fee hovers below 50%, mainly due to the fact many cases are identified at superior degrees. Catching the disorder early is critical for improving survival prices on the grounds that treatment is commonly more powerful and less invasive at in advance tiers. Despite advances in medical generation, diagnosing oral most cancers remains hard, largely because it frequently offers without symptoms in its early phases and distinguishing malignant lesions from benign conditions can be problematic. [1]

The conventional techniques for detecting oral cancer—visible inspection, biopsy, and histopathology—are nevertheless the gold general. However, these techniques have barriers. Visual checks may pass over subtle early-stage lesions or miss out on precancerous situations, at the same time as biopsies are invasive, time-eating, and can purpose soreness. They additionally require specialized system and professional specialists, making them less reachable in low-useful resource regions. Non-invasive imaging technologies, together with MRI, CT scans, and Optical Coherence Tomography (OCT), have emerged as alternatives for visualizing oral lesions. However, decoding these pictures as it should be calls for widespread understanding, and the variety in lesion appearance complicates prognosis.

In current years, the combination of increased computational electricity and improvements in artificial intelligence (AI) has brought about the development of effective gear for scientific picture evaluation. Deep learning algorithms, especially Convolutional Neural Networks (CNNs), have achieved tremendous success in regions like image category, segmentation, and item detection. CNNs are specifically applicable to medical imaging responsibilities due to the fact they are able to automatically examine hierarchical features from raw photo information, allowing them to hit upon complex styles and textures. When implemented to cancer detection, CNNs can enhance both the accuracy of diagnoses and the speed of photograph analysis. [2]

Recent studies have investigated numerous gadget mastering and deep gaining knowledge of strategies for detecting and classifying oral cancer. Traditional picture processing techniques—which include thresholding, edge detection, and morphological operations—have been used to phase cancerous regions from healthful tissue. [3] However, these techniques regularly struggle with the range in lesion appearance, size, and texture from one patient to another. Additionally, they rely heavily on manually designed features, which won't absolutely seize the complexity of cancerous lesions. As a result, there is growing hobby in statistics-pushed methods, specifically deep getting to know, which could routinely research relevant features from huge datasets and adapt to the numerous displays of oral cancer photos.

# Literature Review

Recent advancements in deep learning techniques have significantly advanced medical image analysis, especially in Oral cancer detection and classification. This review synthesizes key contributions and methodologies in this field.

﻿1. Traditional Methods for Oral Cancer Detection

Historically, oral cancer prognosis depended on clinical exam and histopathological analysis following tissue biopsy. Visual examination of lesions by using clinicians, combined with patient-suggested signs, has been the initial step in detecting oral most cancers [4]. However, those methods are subjective, frequently resulting in overdue-degree analysis. In an attempt to improve early detection, photo processing techniques along with thresholding, facet detection, and place-based segmentation have been introduced to locate oral lesions in diverse imaging modalities together with MRI, CT, and OCT.

While those techniques supplied treasured insights, they exhibited obstacles, especially in differentiating between healthful tissue and malignancies. Furthermore, variability in lesion morphology, length, and texture throughout patients appreciably impacted the overall performance of those methods, resulting in lower sensitivity and specificity. Threshold-primarily based strategies, for instance, struggled with the inherent noise and choppy illumination found in many medical photos.

2. Machine Learning-Based Approaches for Oral Cancer Detection

The emergence of gadget getting to know opened new avenues for enhancing segmentation and class duties in medical imaging. Feature-based totally machine mastering fashions, along with assist vector machines (SVMs) and random forests, have been hired to categorise oral lesions using hand made functions. These fashions accomplished nicely in unique eventualities however have been noticeably dependent on the exceptional of the function extraction system. Features consisting of texture, depth, and shape descriptors had been manually selected, regularly requiring area understanding and substantial preprocessing. [5]

[5]For example, Khandpur et al. (2015) evolved an SVM-based version for the type of oral cancer using histopathological pix. Their technique employed texture and morphological functions, attaining moderate accuracy in differentiating among malignant and benign lesions. However, the version's reliance on hand made capabilities constrained its generalizability to more complex, actual-global datasets.

3. Deep Learning for Medical Image Segmentation

Deep getting to know, mainly Convolutional Neural Networks (CNNs), has revolutionized clinical picture evaluation through automatically getting to know relevant features from uncooked photograph data, bypassing the need for guide characteristic engineering. CNNs had been widely followed for segmentation responsibilities in most cancers detection, providing superior overall performance in terms of accuracy and performance. In the context of oral most cancers, several studies have verified the efficacy of CNNs for delineating cancerous regions from surrounding tissues.

For instance, Shao et al. (2019) carried out a U-Net architecture for the segmentation of oral cancer areas in MRI pix. The U-Net version, characterised through its encoder-decoder shape, efficaciously captured the spatial context of lesions, accomplishing contemporary results in phrases of segmentation accuracy. Similarly, Zhang et al. (2021) explored the usage of a ResNet-based CNN for segmentation of oral most cancers in OCT photos, reporting giant improvements over traditional segmentation strategies. These studies spotlight the robustness of CNNs in dealing with the range inherent in scientific pics, which include noise and lighting fixtures inconsistencies.

4. Deep Learning for Classification of Oral Cancer

In parallel with advancements in segmentation, deep gaining knowledge of has additionally made giant strides inside the category of cancerous lesions. CNNs were employed to classify oral cancer based totally on features routinely extracted from segmented areas. Typically, deep studying-based class fashions are educated on big datasets of medical photographs, letting them examine discriminative capabilities that distinguish between one of a kind levels and forms of most cancers.

One fantastic have a look at through Sun et al. (2020) brought a hybrid model combining a CNN with a Long Short-Term Memory (LSTM) community for classifying oral most cancers ranges. [6] Their model used temporal records from sequential imaging statistics to improve classification accuracy, demonstrating that deep studying ought to capture complicated styles related to most cancers development. Other methods, along with switch getting to know, had been applied to deal with the issue of confined labeled datasets in the clinical area. Pre-skilled fashions on large photo datasets, inclusive of ImageNet, are first-class-tuned on smaller, domain-unique datasets, resulting in progressed performance inspite of confined information availability.

5. Challenges and Limitations

Despite the big progress made in applying deep mastering to oral cancer detection, numerous demanding situations stay. One of the primary problems is the lack of huge, annotated datasets required to train deep gaining knowledge of fashions effectively. [7]The annotation of medical photographs is exertions-extensive and requires professional understanding, making it hard to reap massive, first rate datasets. As a result, models trained on small datasets can also suffer from overfitting and shortage generalizability throughout diverse populations and imaging modalities.

# METHODOLOGY

The proposed methodology includes data collection, data preprocessing, convolution neural network, model training and evaluation.

## Data Collection

﻿The dataset used in this observe includes medical snap shots of the oral cavity, mostly specializing in areas with potential cancerous lesions. Data is sourced from publicly to be had medical photo repositories as well as participating healthcare establishments, providing pictures of various stages of oral cancer. [8] & [9]This dataset includes:

Imaging Modalities: Optical coherence tomography (OCT), magnetic resonance imaging (MRI), and histopathology pix.

Categories: Images are annotated into categories including benign, pre-cancerous, and malignant lesions, along side distinctive most cancers degrees (Stage I, II, III, IV).

Data Volume: Approximately 1,500 to 2,000 snap shots have been accumulated, making sure a various range of cancerous and non-cancerous tissue samples.

Challenges in Data Collection:

Variability in photograph exceptional across assets (special resolutions and noise tiers).

Annotation consistency, requiring professional validation for correct labeling

## Data preprocessing

﻿To make certain consistency and satisfactory inside the enter facts, numerous preprocessing techniques had been carried out. Preprocessing is vital for improving version performance, in particular for medical imaging, where variability can drastically affect segmentation and type results.

Preprocessing Steps:

Resizing: All pictures are resized to a uniform dimension

(256x256 pixels) to ensure that they can be processed correctly via the CNN. [10]

Normalization: Pixel intensity values are normalized to the variety [0,1] to reduce the impact of varying illumination conditions and ensure that the neural community learns significant patterns as opposed to being motivated by way of depth variations.

Data Augmentation: Since the dataset is quite small, statistics augmentation techniques are employed to artificially amplify the dataset. This includes random rotations, flipping, scaling, and shifting to introduce variability and improve generalization in the course of version training.

Noise Removal: Median filtering and Gaussian blurring are implemented to lessen picture noise at the same time as retaining the critical functions wanted for segmentation.

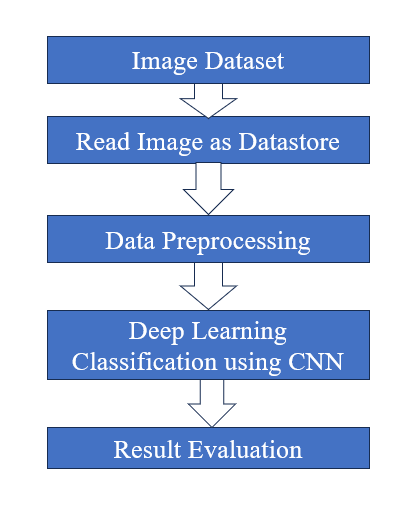


Fig. 1. Flowgraph of the proposed work

## Convolution Neural Network (CNN) Model

﻿The segmentation and category framework is constructed on a deep CNN structure due to its established effectiveness in scientific photograph analysis, [11]particularly for tasks inclusive of object detection, segmentation, and classification. The proposed model makes use of a U-Net structure for segmentation and a class CNN for identifying cancer degrees.

CNN for Segmentation (U-Net):

U-Net Architecture: U-Net is a widely used architecture for clinical image segmentation. It consists of an encoder-decoder structure:

Encoder: The encoder consists of a couple of convolutional layers and max-pooling layers to extract high-degree capabilities from the enter photographs.

Decoder: The decoder up samples the function maps to reconstruct a segmented photograph of the unique resolution, using bypass connections to combine excessive-resolution capabilities from the encoder.

Output: The final output is a binary masks wherein cancerous areas are prominent from wholesome tissues.

CNN for Classification:

Feature Extraction: After segmentation, features inclusive of texture, shape, and depth are extracted from the segmented areas. Additionally, the CNN routinely learns abstract functions from the segmented pictures.

Classification Layers: The category network includes absolutely linked layers and soft-max activation to predict the stage or type of cancer (squamous cellular carcinoma, verrucous carcinoma).

Multi-Class Output: The output layer classifies the lesion into multiple classes, such as benign, Stage I, II, III, or IV oral cancer. [12]

|  |  |  |
| --- | --- | --- |
| **Layer** | **Output Shape**  **(H, W,C)** | **Param** |
| Convolution2D\_1 | 240,240,3 | 0 |
| Convolution2D\_2 | 119,119,32 | 869 |
| MaxPooling2D\_1 | 59,59,32 | 0 |
| Convolution2D\_3 | 29,29,32 | 9248 |
| Convolution2D\_4 | 14,14,32 | 0 |
| MaxPooling2D\_2 | 14,14,32 | 0 |
| flatten (Flatten) | None,6272 | 0 |
| dense (Dense) | None, 64 | 401472 |
| Dropout (dropout) | None, 64 | 0 |
| Dense\_1 (dense) | None,1 | 65 |

1. MODEL SUMMARY OF PROPOSED WORK

VGG16

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

Layer (type) Output Shape Param #

=================================================================

input\_2 (InputLayer) [(None, 240, 240, 3)] 0

block1\_conv1 (Conv2D) (None, 240, 240, 64) 1792

block1\_conv2 (Conv2D) (None, 240, 240, 64) 36928

block1\_pool (MaxPooling2D) (None, 120, 120, 64) 0

block2\_conv1 (Conv2D) (None, 120, 120, 128) 73856

block2\_conv2 (Conv2D) (None, 120, 120, 128) 147584

block2\_pool (MaxPooling2D) (None, 60, 60, 128) 0

block3\_conv1 (Conv2D) (None, 60, 60, 256) 295168

block3\_conv2 (Conv2D) (None, 60, 60, 256) 590080

block3\_conv3 (Conv2D) (None, 60, 60, 256) 590080

block3\_pool (MaxPooling2D) (None, 30, 30, 256) 0

block4\_conv1 (Conv2D) (None, 30, 30, 512) 1180160

block4\_conv2 (Conv2D) (None, 30, 30, 512) 2359808

block4\_conv3 (Conv2D) (None, 30, 30, 512) 2359808

block4\_pool (MaxPooling2D) (None, 15, 15, 512) 0

block5\_conv1 (Conv2D) (None, 15, 15, 512) 2359808

block5\_conv2 (Conv2D) (None, 15, 15, 512) 2359808

block5\_conv3 (Conv2D) (None, 15, 15, 512) 2359808

block5\_pool (MaxPooling2D) (None, 7, 7, 512) 0

flatten\_1 (Flatten) (None, 25088) 0

dense\_2 (Dense) (None, 64) 1605696

dropout\_1 (Dropout) (None, 64) 0

dense\_3 (Dense) (None, 1) 65

The final fully connected layer contains 4 neurons and utilizes a softmax activation function, making it ideal for multi-class classification tasks. The softmax function generates probability scores for each class, with the highest score representing the predicted class. [13]

## Model Training and Evaluation

﻿Model schooling is split into levels: segmentation education and type training. Each section includes tuning the CNN architecture, optimizing hyperparameters, and the use of loss functions appropriate to every undertaking.

Segmentation Training:

Loss Function: For segmentation, the Dice loss is used. This loss function is well-acceptable for photo segmentation because it specializes in the overlap among the expected segmentation and the ground reality, making sure correct delineation of cancerous areas.

Optimizer: The Adam optimizer is used to replace network weights. Adam is selected for its adaptive studying fee skills, which speeds up convergence whilst preserving balance.

Training Dataset: 80% of the facts is used for training the model, with the final 20% reserved for validation to save you overfitting. [14]

Classification Training:

Loss Function: For category, express pass-entropy is carried out, as it's miles the standard for multi-class classification troubles. This loss characteristic penalizes the model based at the distinction between anticipated and true labels.

Batch Size and Epochs: The model is skilled using a batch length of 32 over 100 epochs. Early preventing is implemented if validation loss plateaus to save you overfitting. [15]

Transfer Learning: Pre-educated CNN fashions (ResNet or VGG) are pleasant-tuned for class tasks to enhance performance, in particular given the confined length of the scientific picture dataset.

# RESULTS AND DISCUSSION

﻿To determine the performance of the proposed framework, several assessment metrics are used to degree each the segmentation and class accuracy.

Segmentation Evaluation:

Dice Coefficient: Measures the overlap between the anticipated mask and the floor fact, with a rating of one indicating perfect segmentation. [16]

Intersection over Union (IoU): Evaluates the ratio of overlap among anticipated and proper regions, imparting a dependable metric for segmentation accuracy.

Classification Evaluation:

Accuracy: The proportion of efficaciously labeled lesions (benign or various cancer ranges) out of the whole predictions.

Sensitivity (Recall): The capability of the model to efficaciously perceive cancerous lesions, ensuring that fake negatives are minimized.

Specificity: Measures the version’s ability to efficiently perceive healthy areas, decreasing the probability of false positives.

F1-Score: A harmonic imply of precision and recollect, balancing the performance of the version in cases of imbalanced datasets.

Cross-Validation:

okay-fold Cross-Validation: We use five-fold go-validation to ensure that the version generalizes well to unseen statistics. This technique facilitates save you overfitting via testing the model on a couple of partitions of the dataset. [17]

Test Set Evaluation: After schooling, the version is evaluated on a separate take a look at set (20% of the dataset) that was not used throughout education to assess its real-global overall performance.

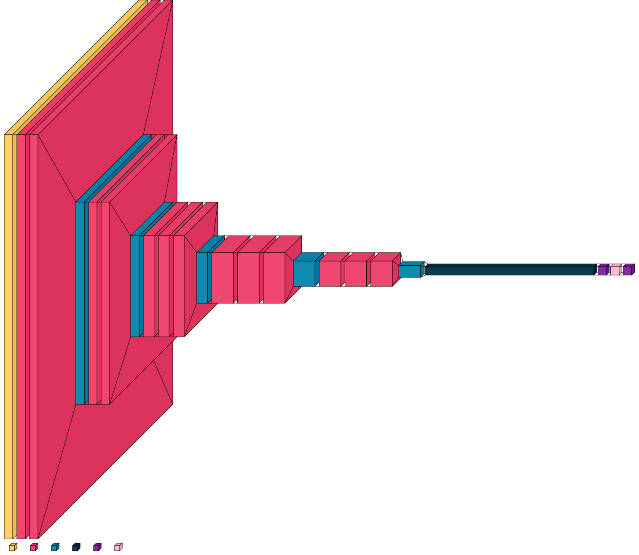


Fig. 2. visualkeras

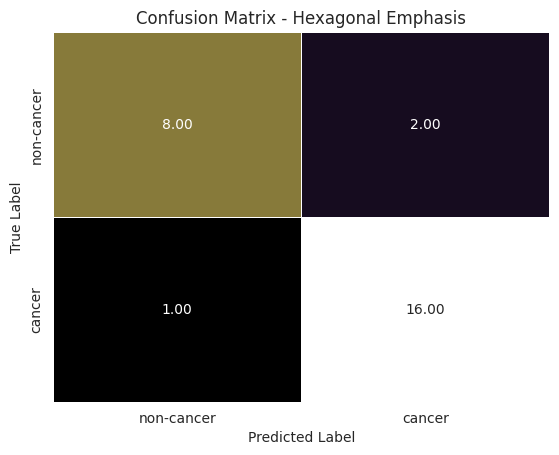


Fig. 3. Confusion Matrix - Hexagonal

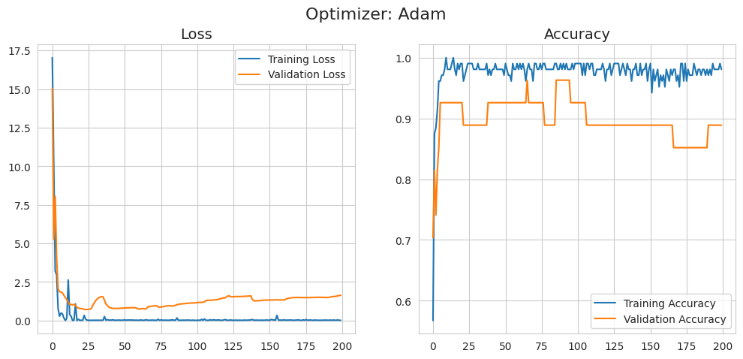


Fig. 4. Loss and Validation Accuracy graph

These results demonstrate that the CNN model achieves high accuracy and good performance across different tumor types. However, further analysis of the confusion matrix a shown in Fig. 2,Fig 3., might reveal areas where the model can be improved, such as reducing misclassifications between certain tumor types [18]

From Fig. 4 , it is evident that the model accuracy increases and loss decreases as epoch increases and given the best epoch which increases efficiency of the model

# CONCLUSION AND FUTURE WORK

In this research paper, we examine the use of deep learning techniques brain tumor classification model using pre-trained deep learning techniques have yielded promising results indicative of its potential in clinical practice. Through the utilization of CNNs, the model demonstrates high precision, recall, and F1-score values across diverse tumor types, including glioma, meningioma, pituitary tumors, and cases without tumors. [19]

The model's exceptional performance metrics underscore its effectiveness in accurately distinguishing between tumor and non-tumor cases, crucial for timely diagnosis and treatment planning. With an overall accuracy of 95%, the model showcases its reliability in clinical decision-making, offering clinicians a valuable tool for enhanced diagnostic accuracy and patient care.

Furthermore, the integration of CNNs with diagnostic imaging modalities such as MRI enhances the interpretability and analysis of medical images, contributing to a more comprehensive understanding of brain tumor characteristics and behaviour. Moving forward, continued research and refinement of deep learning models for brain tumor classification hold immense potential for advancing the field of neuro-oncology. Further optimization of model architectures, incorporation of multi-modal imaging data, and exploration of novel deep learning techniques can further enhance the accuracy and robustness of brain tumor classification models. [20] & [21]

In summary, the presented brain tumor classification model represents a significant step towards improving diagnostic accuracy and patient outcomes in neuro-oncology. By harnessing the power of deep learning and leveraging vast amounts of medical imaging data, the model offers a promising avenue for enhancing clinical decision support and personalized treatment strategies in the management of brain tumors.

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