AI-Powered Web Application for Oral Cancer Detection and Treatment Recommendation Using CNN on MRI, CT, and PET Scans

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Abstract: Oral cancer is a serious disease that requires early detection to improve patient survival. Traditional diagnostic methods such as visual screening and biopsy are time-consuming and uncomfortable for patients. This project presents an automated oral cancer detection system using medical images and a Binary Convolutional Neural Network (Binary CNN). The system analyzes oral region scan images and classifies them into two categories: cancerous and non-cancerous. Image preprocessing techniques improve quality before feature extraction.

The Binary CNN automatically learns tumor-related patterns and performs accurate classification. The system focuses only on oral cancer detection and does not include multi-disease analysis. This approach reduces manual effort, supports faster diagnosis, and assists medical professionals in early screening using a simple and reliable computer-based detection system.

Keywords - Oral Cancer Detection , Binary CNN, Medical Image Classification , Cancer Screening

Introduction: Oral cancer is one of the most common and life-threatening cancers worldwide, with a higher occurrence in developing countries due to tobacco consumption, alcohol use, and poor oral hygiene. The survival rate of patients largely depends on early detection, but most cases are identified at advanced stages. Conventional diagnostic methods such as visual examination and biopsy are invasive, subjective, and time-consuming. These drawbacks create the need for an automated, accurate, and non-invasive system that can assist in early diagnosis and effective treatment planning.

Medical imaging techniques such as MRI, CT, and PET scans provide detailed internal views of oral tissues and tumor structures. These imaging modalities help in identifying abnormalities, lesion size, and tissue variations. However, manual analysis of these images requires expert knowledge and may lead to human error or delayed diagnosis. Therefore, an automated image analysis approach is required to improve diagnostic speed and accuracy.

Convolutional Neural Networks (CNN) have shown excellent performance in medical image analysis by automatically extracting important features from images. CNN models can identify complex patterns in MRI, CT, and PET images and classify tissues as normal or cancerous. Integrating CNN with medical imaging supports early detection, continuous monitoring, and better treatment decisions in clinical practice.

Problem statement

Oral cancer cases are increasing rapidly, and early detection remains a major challenge. Manual diagnosis using clinical examination and biopsy is slow, invasive, and dependent on specialist expertise. Medical image interpretation may also lead to human error and delayed decisions. There is a need for an automated system that can accurately detect oral cancer using medical images. The system must focus only on oral cancer and provide reliable classification into cancerous and non-cancerous cases using an efficient Binary CNN algorithm.

Literature Survey

Xiaoxuan Liu [1], In this systematic review and meta-analysis, we searched Ovid-MEDLINE, Embase, Science Citation Index, and Conference Proceedings Citation Index for studies published from Jan 1, 2012, to June 6, 2019. Studies comparing the diagnostic performance of deep learning models and health-care professionals based on medical imaging, for any disease, were included. We excluded studies that used medical waveform data graphics material or investigated the accuracy of image segmentation rather than disease classification.

Vivek Borse [2], This review describes various risk factors related to the occurrence of oral cancer, the statistics of the distribution of oral cancer in India by various virtues, and the socio-economic positions. The various conventional diagnostic techniques used routinely for detection of the oral cancer are discussed along with advanced techniques. This review also focusses on the novel techniques developed by Indian researchers that have huge potential for application in oral cancer diagnosis.

Kritsasith Warin [3], Fifty-four qualified for inclusion, including diagnostic (n = 51), and prognostic prediction (n = 3). Thirteen studies showed a low risk of biases in all domains, and 40 studies low risk for concerns regarding applicability. The per formance of DL models was reported of the accuracy of 85.0–100%, F1-score of 79.31 - 89.0%, Dice coefficient index of 76.0 - 96.3% and Concordance index of 0.78–0.95 for classification, object detection, segmentation, and prognostic prediction, respectively. The pooled diagnostic odds ratios were 2549.08 (95% CI 410.77–4687.39) for classification studies.

BOFAN SONG [4], With the goal to screen high-risk populations for oral cancer in low- and middle income countries (LMICs), we have developed a low-cost, portable, easy to use smartphone based intraoral dual-modality imaging platform. In this paper we present an image classification approach based on autofluorescence and white light images using deep learning methods. The information from the autofluorescence and white light image pair is extracted, calculated, and fused to feed the deep learning neural networks. We have investigated and compared the performance of different convolutional neural networks, transfer learning, and several regularization techniques for oral cancer classification. Our experimental results demonstrate the effectiveness of deep learning methods in classifying dual-modal images for oral cancer detection.

Rachit Kumar Gupta [5], The dataset under taken for the study consists of 672 tissue images of epithelial squamous layer of oral cavity captured out of the biopsy samples of 52 patients. After applying the data pre-processing and augmentation on the given dataset, 2688 images were created. Further, these 2688 images were classified into 4 categories with the help of expert Oral Pathologist. The classified data was supplied to the convolutional neural network for training and testing of the proposed framework. It has been observed that training data shows 91.65% accuracy whereas the testing data achieves 89.3% accuracy. The results produced by our proposed framework are also tested and validated by comparing the manual results produced by the medical experts working in this area.

Swati Sharma [6], Secondary data on age-adjusted rates (AARs) of incidence of oral cancer and other associated sites for all ages (0–75 years) were collected from the report of the National Cancer Registry Programme 2012–2014 in 29 population-based control registries. Results: Among both males and females, mouth cancer had maximum Age adjusted incidence rates (64.8) in the central zone, while oropharynx cancer had minimum AAR (0) in all regions. Conclusion: Oral cancer incidence increases with age with typical pattern of cancer of associated sites of oral cavity seen in the northeast region.

Existing system

The existing system relies on visual examination, biopsy tests, and manual analysis of medical scans. These methods are time-consuming and require experienced doctors. Biopsy procedures are invasive and may cause patient discomfort. Manual image interpretation can lead to misdiagnosis and inconsistent results. Most healthcare centers do not have automated tools dedicated specifically to oral cancer detection. There is limited use of binary image classification systems designed for single-disease diagnosis.

Methodology:

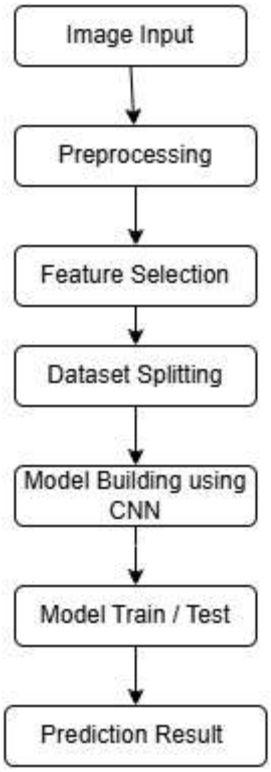

Fig 1 : Block Diagram

1. Image Input

Medical images of the oral region are collected and uploaded into the system. These images contain samples of cancerous and non-cancerous tissues.

2. Preprocessing

Input images are cleaned and prepared for analysis. Noise is removed, images are resized to a fixed dimension, normalized, and enhanced to improve quality.

3. Feature Selection

Important visual patterns such as tumor shape, texture, edges, and abnormal tissue regions are identified. This step ensures that only meaningful information is used for learning.

4. Dataset Splitting

The dataset is divided into training and testing sets.

- Training set — used to teach the model
- Testing set — used to evaluate performance

5. Model Building using CNN

A Binary Convolutional Neural Network model is constructed with convolution, pooling, and fully connected layers to learn image features automatically.

6. Model Train / Test

The CNN model is trained using labeled images. After training, the model is tested with unseen images to measure accuracy and performance.

7. Prediction Result

The trained model predicts whether the input image belongs to:

- Cancerous (Oral Cancer Present)
- Non-Cancerous (Normal)

Algorithm

A Binary Convolutional Neural Network (Binary CNN) is used to classify oral cancer images into two classes: cancerous and non-cancerous. The algorithm automatically learns important image features without manual intervention.

Working Process:

Convolution Layer
Filters scan the image to detect tumor-related patterns like edges, textures, and abnormal regions.

Activation Function (ReLU)
Adds non-linearity so the network can learn complex medical image patterns.

Pooling Layer
Reduces feature map size to lower computation while keeping important information.

Deep Feature Extraction
Multiple convolution layers learn high-level representations of cancer tissues.

Flattening
2D feature maps are converted into a 1D vector.

Fully Connected Layers
Features are analyzed to make classification decisions.

Output Layer (Sigmoid Function)
Produces probability score and classifies image into:

- 1 — Cancerous
- 0 — Non-Cancerous

Dataset
The dataset used in this system consists of medical imaging data specifically collected for **oral cancer diagnosis**. It includes three major imaging modalities: **PET (Positron Emission Tomography) scans**, **CT (Computed Tomography) scans**, and **MRI**

(Magnetic Resonance Imaging) scans of the oral and head–neck region. These imaging techniques provide complementary information—PET scans highlight metabolic activity of cancerous tissues, CT scans capture detailed bone and structural anatomy, and MRI scans provide high-resolution soft tissue contrast. The dataset contains only oral cancer–related images, including both malignant and benign tumor cases, ensuring disease-specific model training. All images are used for preprocessing, feature extraction, training, and testing of the Binary CNN model to enable accurate and automated cancer classification.

Mathematical Model

Let the input medical image dataset be:

$$\mathbf{D = \{I_1, I_2, I_3, \ldots, I_n\}}$$

where *I* represents oral cancer images.

1. Preprocessing

Each image is resized and normalized:
I' = Normalize(Resize(I))

2. Convolution Operation

Feature extraction using filters:
$$\mathbf{F = I' \otimes K + b}$$
where
$\otimes$ = convolution operation
K = kernel/filter
b = bias
F = feature map

3. Activation Function (ReLU)

A = max(0, F)

4. Pooling

Dimensionality reduction:
P = Pool(A)

5. Flattening

Convert matrix to vector:
V = Flatten(P)

6. Fully Connected Layer

$$\mathbf{Z = W \cdot V + b}$$

7. **Output Layer (Sigmoid — Binary Classification)**

$$\mathbf{\hat{y} = 1 / (1 + e^{-z})}$$

8. Decision Rule

If $\hat{y} \geq$ **0.5 → Cancerous**
If $\hat{y} <$ **0.5 → Non-Cancerous**

Results and Discussion

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(A)

(B)

(C)

(D)

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(F)

(G)

(H)

Fig 2: Pages

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