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ORAL CANCER DETECTION USING DEEP LEARNING

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Abstract: Oral cancer is a very serious, complex, and common type of cancer. Oral cancer ranks eighth globally in terms of cancer incidence in India, with 130,000 deaths reported annually. The tumor affects the tonsils, salivary glands, neck, face, and mouth. Numerous methods, including as screening procedures and biopsies—which entail taking a small sample of body tissue and analyzing it under a microscope—can be used to identify oral cancer. The disadvantage of cancer cells is that they are hard to identify and quantify. For this reason, digital processing technology will be employed in this study to identify and classify cancer cells that have affected the oral cavity. State-of-the-art technology and an in-depth learning algorithm can be employed for early detection and categorization. This work employs the Zernike Moment, wavelet features, and the bag histogram of directed gradients as three techniques for character extraction. After the characteristics are obtained, the best texture characteristic is chosen using the fuzzy particle swarm optimization technique (FPSO). In the end, these features were classified using the Faster Region based Convolution Neural Network (faster RCNN) classifier. to evaluate the efficiency, error, recall rate, precision rate, and classification accuracy of the recommended approach.

Keywords: GUI, faster region-based convolution neural network (RCNN) classifier, and fuzzy particle swarm optimization algorithm (FPSO).

I. INTRODUCTION

It has been discovered that the cells supplying injured neighboring tissues exhibit uncontrolled increased growth in mouth cancer. Less dead cells are discovered in the oral tissue at the early stages of oral cancer development, also referred to as ulcers. when the body's metabolism reveals the existence of dead cells, either throughout the affected area or in discrete areas. Although there are other forms of cancer, 90% of crab cells are referred to in medical terms as OSCCs, or oral squamous cell carcinomas. In addition to clinical forms of linked and lesion-free tumour models, biological models can be used to identify cancers in different sections of the body utilizing appearance models and stereotypes without staining. Before samples were evaluated for the oral cancer stage, machine learning techniques were used to predict distinct biological models for OSCC. These models would classify samples as either malignant or non-cancerous. To evaluate the accuracy of the interaction, the predictor will make use of three justification test kits and different stages of cancer. Sampling with sample justification can help forecast diverse phases of oral cancer by predicting the creation of ulcers in the tissues and variable tumor sizes. The primary goal of the current procedure is to develop new tools for predicting the growth stage of oral cancer tumors. Oral cancer can grow in a number of places, including the gums, the back of the wisdom teeth, the inside of the cheeks and lips, the upper and lower regions of the mouth, and the front of the tongue. Oral cancer symptoms include: The majority of cancer symptoms are persistent ulcers or inflammations that might bleed or cause pain. There are numerous behaviors that raise the risk of oral cancer, including smoking and alcohol consumption. There is measurement of the two behaviors that pose the greatest risk for mouth cancer. Eating worms is so common in India that it also harms the inside of the gums.

Faster R-CNN: Region Based CNNs

Given that a fully connected layer of a convolution neural network (CNN) cannot handle many items and occurrence frequency. One method, therefore, would be to apply the CNN model to a region that has been selected via a sliding window brute force search. However, this approach has the drawback that the same item may be represented in images with varying aspect ratios and sizes. We have several region ideas when taking these parameters into account, and applying deep learning (CNN) to all of those regions would be quite costly computationally.

A two-stage deep learning object detector is used by the Faster R-CNN; first, it finds regions of interest, and then it sends these regions to a convolutional neural network. A support vector machine (SVM) is used to classify the feature maps that are produced. It is calculated to find the regression between the expected and ground truth bounding boxes. The Faster R-CNN's general architecture is shown below. The Faster R-CNN model employs the subsequent methodology: The ground truth bounding boxes of the picture are projected onto the feature map after the image has initially passed through the backbone network to produce an output feature map. Typically, a dense convolutional network such as ResNet or VGG16 serves as the backbone. The learnt features of the image are represented by a spatially dense Tensor in the output feature map. Every point on this feature map is then treated as an anchor. We create several boxes of various sizes and forms for every anchor. These anchor boxes are meant to capture things within the picture.

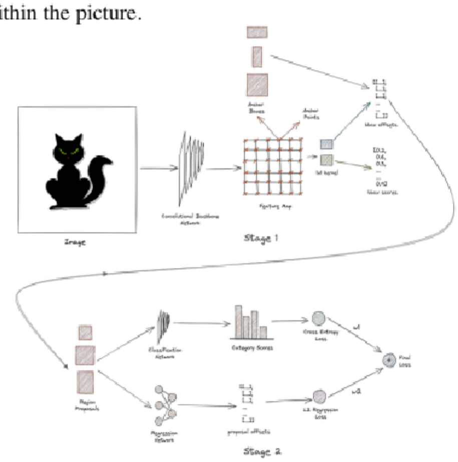


Fig1. Faster R-CNN Overall Architecture

Stage 2 is informed by the ideas from the first stage region. In step 2, we learn to predict the category of the object in the region suggestion using a simple convolutional network. We use a technique called ROI pooling to scale the raw region suggestions, which now come in a range of sizes, before transmitting them across the network. This network learns how to predict different categories via cross-entropy loss. We use a second network to predict offsets of area proposals from ground truth boxes. Additionally, this network looks to match region recommendations with ground truth boxes. This makes advantage of L2 regression loss. Weighing the total of the two losses allows us to determine the final loss. We learn how to forecast offsets in addition to categories in Stage 2. This is known as multitask learning.

II. PROBLEM STATEMENT

The current state of oral cancer diagnosis faces challenges in early detection and accurate categorization of tumours, hindering effective treatment and prognosis. Oral cancer, particularly Oral Squamous Cell Carcinomas (OSCC), manifests as uncontrollable cell enlargement, often detected at later stages through symptoms like inflammation and non-healing ulcers in oral tissues. Existing methods rely on biological and clinical models, including machine learning approaches, to predict different biological OSCC models and distinguish between non-cancerous and malignant samples. However, there is a need for an improved predictive tool that can precisely determine the stage of oral cancer growth. The challenge lies in developing robust predictive models capable of assessing tumour volume and identifying the presence of ulcers in oral tissues across various anatomical locations. Therefore, the challenge at hand is to develop and put into use a sophisticated predictive tool that uses biological models, clinical data, and machine learning approaches to reliably classify oral cancer stages according to tumour volume and ulcer existence.

III. OBJECTIVES

- Collect the dataset from Kaggle Website (open source) and few Real dataset from RND for implementation.
- To develop Robust Predictive Model for oral cancer detection.
- Apply Deep Learning Algorithm to the model for effective validation.

IV. METHODOLOGY

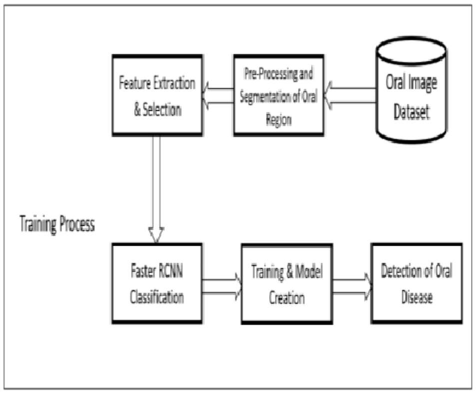


Fig2. Proposed Training System

The above figure depicts the general workflow for this project. The training process is depicted on the figure's upper side. All training oral cancer photos and relevant cancer kinds are included in the sample database. Next, take features from the areas affected by oral cancer. The retrieved characteristics are used to train the classifier model, which is then stored for further use. The testing process is depicted on the lower side of Figure 2.

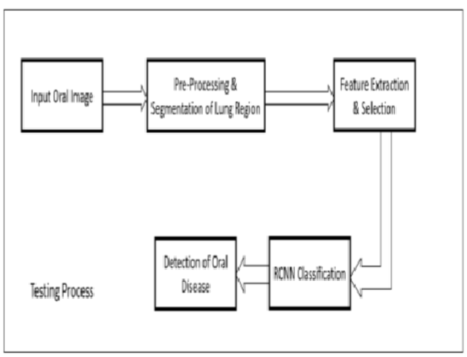
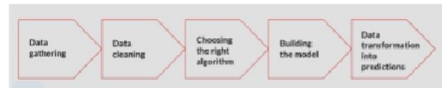


Fig3.Proposed Testing System

Figure 3 illustrates the testing system where samples undergo pre-processing methods to reduce noise and enhance clarity. After pre-processing, segmentation comes next. In order to calculate the unique features, all of the techniques are combined to retrieve features like texture and intensity. To shorten the execution time, a suitable feature is chosen after the features have been retrieved. Eventually, the chosen qualities are used to identify the disease and its effects. Finally, the Faster RCNN approach is used to classify and train the features.

A. System Design



1. *Data Collection:* The method of data collection varies depending on the kind of project we want to create. For example, we can create an Internet of Things system that utilizes various sensor data if we want to create an ML project that uses real-time data. The data set can be gathered from a variety of sources, including files, databases, sensors, and many more. However, because there may be a lot of missing data, excessively big values, disorganized text data, or noisy data, the obtained data cannot be used directly to carry out the analysis process. As a result, data preparation is done to address this issue.

2. *Data Pre-Processing:* The first step in data pre-processing is to clean the raw data, which is obtained from real-world data collection and transformed into a clean data set. Put another way, any time data is collected in an unprocessed format from several sources, it isn't suitable for analysis. As a result, a series of actions are taken to reduce the data to a manageable, clean data set; this phase of the procedure is known as data pre-processing.

3. *Investigating the Best Model for the Type of Data:* Using the pre-processed data, our primary objective is to train the best performing model available.

4. *Using Data to Train and Test the Model*: The first step in training a model is to divide it into three sections: testing, validation, and training data. The "training data set" is used to train the classifier; the "validation set" is used to fine-tune the parameters; and the "test data set" is used to evaluate the classifier's performance on unseen data. It's crucial to remember that the classifier can only be trained using the training and/or validation sets. The classifier cannot be trained using the test data set. Tests are the only times the test set will be accessible.

B. Module Design

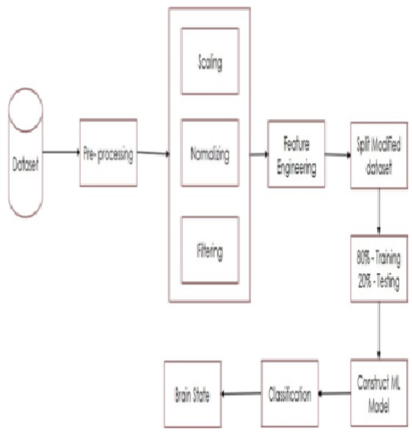


Fig4. Module Design

The above diagram shows the proposed system flow diagram. The input raw data is taken and under gone the pre-processing technique where the data are scaled, normalised and filtered. Then they are split for training and testing purpose. After which the ML model is constructed and classified. After which the brain state is classified for given dataset.

C. Unit Design

Figure5. shows the unit diagram of proposed system. The client or the user is respectively responsible for collecting the datasets and uses for training. Then the input variables are selected and gives the general output of model accuracy and loss. Then the model is trained accordingly.

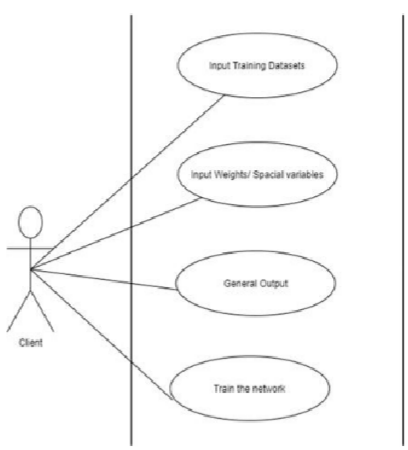


Fig5. Unit Design

D. UML Design

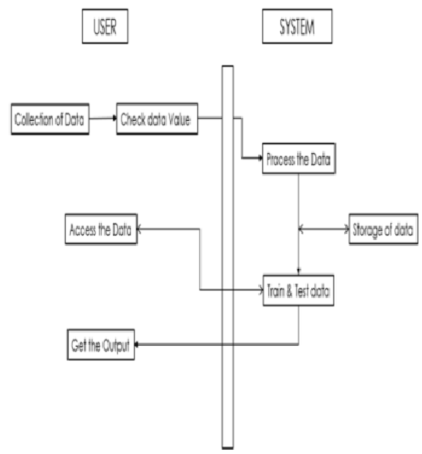


Fig6. UML Design

The UML design shows the step-by-step operations with respect to the user and system. The complete integration is shown above. The user is responsible for the data collection and how the processing is done. Also, it is responsible for accessing the data. The system processes the data and stores it. The training and testing steps are followed here and gives the output in either vales or graphical format.

E. Workflow

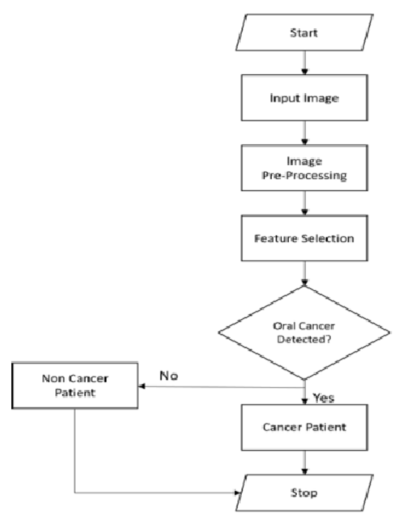


Fig7. Workflow of Project

V. RESULT

A. *Faster RCNN Training*

Training process is crucial to monitor the model's performance and adjust hyperparameters as needed to ensure optimal training and convergence. The model is trained with multiple epochs until the convergence or the validation loss stabilizes.

B. *Fuzzy Optimization Training*

Fuzzy optimization can effectively handle uncertainties, imprecisions, and qualitative information, leading to robust and adaptive solutions for complex optimization problems. The images data is trained and generated with ML model with different epochs.

A comparison of both methods' training accuracy over a range of epoch values is shown in Tables 1 and 2. Metrics like precision, recall, and error rates are also computed and presented.

$$Precision\ Rate = \frac{TP}{TP + FP}$$

$$Recall\ Rate = \frac{TP}{TP + FN}$$

Where,

- The term "True Positives" (TP) denotes the quantity of accurately classified positive cases.
- The number of positively identified events that are mistakenly represented by P (False Positives).
- The amount of positive cases that are mistakenly labeled as negative is known as False Negatives, or FN for short.

No.	Epoch	Accuracy	Precision Rate	Recall Rate	Error Rate
1	30	86.6	1	66.6	27.7
2	50	89.5	1	68.3	26.3
3	70	93.7	1	63.3	22.6
4	90	97.2	1	66.6	20.5
5	100	98.8	1	63.4	20.1

Table 1. Training Phase Values of Faster RCNN Model

No.	Epoch	Accuracy	Precision Rate	Recall Rate	Error Rate
1	30	82.6	1	68.5	29.4
2	50	86.4	1	66.3	26.6
3	70	89.7	1	65.2	26.3
4	90	92.3	1	67.7	25.1
5	100	93.6	1	61.1	23.9

Table 2. Training Phase Values of Fuzzy Model

C. *Testing Phase*

In order to enhance user accessibility, a Graphical User Interface (GUI) has been developed for the model or proposed work. This implementation enables users to effortlessly run or test images. Utilizing Python's tkinter library, the GUI is designed to facilitate the testing phase. Figure 9 illustrates the GUI component of the project. The GUI contains specific buttons and predefined actions, illustrated in the figures below.

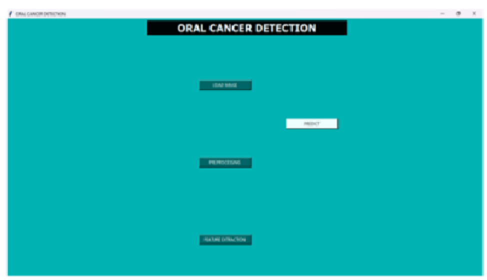


Fig8. Python GUI for Oral Cancer Detection

Overall, the expected outcome is a system capable of accurately earlier detection of oral cancer cells using advanced digital processing techniques and deep learning algorithms, with the efficiency of the system evaluated through various performance metrics

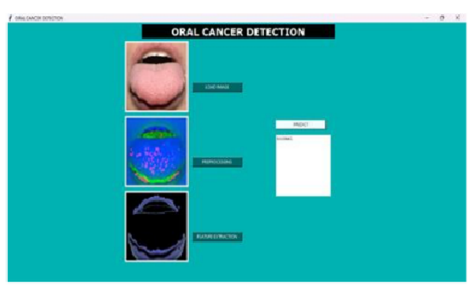


Fig9. Prediction of Normal Condition

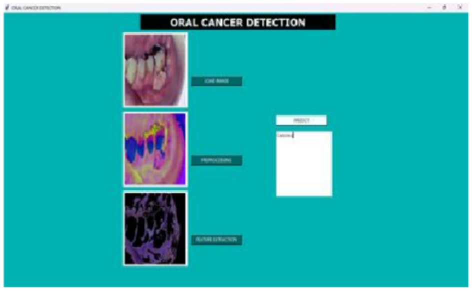


Fig10. Prediction of Oral Cancer Condition

VI. Conclusion

Especially in India, where it is the eighth most frequent cancer and causes a large number of fatalities annually, oral cancer is a major worldwide health concern. Effective diagnostic techniques are required due to the complexity and severity of oral cancer, since conventional methods such as biopsies and screenings are not always able to accurately identify and categorize cancer cells. In order to overcome these obstacles, our work uses digital processing technologies to identify and categorize cancer cells in the oral cavity early on. The combination of cutting-edge technologies and an intelligent learning algorithm shows a viable path toward improving diagnostic abilities. The efficiency of classification can be improved by using Faster RCNN for the extracted characteristics.

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