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Automated Detection of Oral Cancer

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ABSTRACT

Oral cancer presents a significant global health challenge, necessitating timely detection to enhance patient prognosis. This study proposes a novel machine learning framework for automated oral cancer detection utilizing digital imaging technology. Our investigation utilizes a diverse dataset comprising oral images collected from individuals across various oral cancer stages and healthy controls. Data preprocessing techniques, including image resizing and normalization, are implemented to preprocess the dataset. Feature extraction is conducted through convolutional neural networks (CNNs), enabling the extraction of salient features from the images automatically. We explore the efficacy of multiple machine learning algorithms, including deep neural networks, for oral cancer detection. These models are trained and evaluated on the dataset, with performance metrics such as accuracy, sensitivity, specificity, and area under the ROC curve (AUC) employed to gauge their effectiveness. Our findings demonstrate promising performance in automating oral cancer detection, showcasing the potential for early diagnosis and intervention. This research contributes to the advancement of intelligent systems for oral cancer screening, offering a non-invasive and cost-effective approach to complement existing diagnostic modalities.

Keywords – Oral Cancer, CNN, Automated detection, Classification.

INTRODUCTION

Oral cancer is a significant global health issue, with its incidence rising steadily in recent years. According to the World Health Organization (WHO), it ranks among the top ten most prevalent cancers worldwide, with approximately 350,000 new cases reported annually. Despite advancements in treatment modalities, the prognosis for oral cancer patients remains poor, largely due to late-stage diagnoses, which limit treatment options and reduce survival rates .

Timely detection of oral cancer is crucial for improving patient outcomes, facilitating prompt intervention, and enhancing treatment effectiveness. Traditional methods of oral cancer detection primarily rely on clinical examination, histopathological analysis of tissue biopsies, and imaging techniques like computed tomography (CT) and magnetic resonance imaging (MRI). While these approaches are effective, they are often invasive, expensive, and require specialized expertise for accurate interpretation .

Recent years have witnessed a growing interest in harnessing machine learning techniques for automated cancer detection and diagnosis, including oral cancer. Machine learning algorithms, particularly those rooted in deep learning, demonstrate promise in analyzing medical images and extracting meaningful patterns and features not easily discernible by the human eye. By training on extensive datasets of annotated images, these algorithms can learn to differentiate between normal and abnormal tissues, potentially facilitating early detection of oral cancer.

This research endeavors to explore the feasibility and efficacy of employing machine learning methodologies for oral cancer detection using digital imaging technology. We present a comprehensive analysis of a dataset comprising oral images sourced from individuals with varying oral cancer stages alongside healthy controls. Through the application of cutting-edge machine learning algorithms, such as convolutional neural networks (CNNs) we investigate their capability to accurately classify oral images and distinguish between cancerous and non-cancerous tissues.

The outcomes of this study bear significant implications for the development of intelligent systems aimed at oral cancer screening. Such systems offer a non-invasive, cost-effective, and potentially more accessible means to complement existing diagnostic techniques. By enabling early detection and intervention, these systems have the potential to substantially enhance patient outcomes and alleviate the burden of oral cancer on healthcare systems globally.

LITERATURE REVIEW

The literature review on automated detection of oral cancer underscores the urgent need for accurate and efficient diagnostic methods to combat this global health challenge. Several studies have explored the potential of deep learning algorithms, particularly convolutional neural networks (CNNs), in leveraging imaging technologies such as optical coherence tomography (OCT) and photographic images for early detection and classification of oral lesions.

Paper name	Year	Author	Methodology	Research Gap	Result
1. Oral Cancer Detection by CNN	2022	Gizem Tanriver, Merva Soluk Tekkesin, and Onur Ergen	The methodology involves using advanced computer vision techniques to analyze photographic images of oral lesions for the purpose of oral cancer screening. This includes tasks such as segmenting the lesion areas, detecting different types of oral lesions, and classifying them based on their risk of progressing into oral cancer. Deep learning algorithms and models like U-Net, YOLOv5, and EfficientNet b4 are used to achieve these tasks. The study also proposes a two-stage model for automated identification of various oral lesion types, which could be deployed as a low-cost, non-invasive, and easy-to-use oral cancer screening tool.	The research gap in this context is the lack of systematic study on how to improve the accuracy of diagnosing oral diseases using handheld smartphone photographic images. This gap highlights the need for more comprehensive research and the development of new oral cancer detection algorithms to provide doctors with a wider variety of options for diagnosis.	So, the average performan ce across both tasks is approxima tely 0.8354, which can be interpreted as 83.54%.
2. A deep learning algorithm for detection of oral cavity	2020	Qiuyun Fua, Yehansen Chene,Zhiha ng LiKaixiong	The study developed a deep neural network architecture that showed high accuracy in identifying OCSCC lesions in photographs. The	The research gap identified in the document is that there is a lack of established	Accuracy of project is 92.4%

squamous cell carcinoma from photographic images: A retrospective study		Lia, Haixiao Zouh, Yong Songi, gkun Wang,Xiqia n Wangk, Yufan Wangl, Jianying Lium, Hui Liun, Sulin Cheno, Ruibin Chenp, Man Zhangd,Jing jing Zhaoq	algorithm also demonstrated good generalization performance across different datasets. The findings suggest that this approach could be effective in improving the diagnosis and assessment of OCSCC lesions, particularly in early-stage cases. Additionally, the algorithm may have potential applications in evaluating the efficacy of non-surgical treatment modalities. The authors highlight the importance of this technology in aiding healthcare professionals in diagnosing and treating OCSCC.	methods for the early detection of oral cavity squamous cell carcinoma (OCSCC) using photographic images. Previous methods relied on clinical experience and specialized instruments, and there was no direct comparison with the deep learning algorithm developed in the study.	
3. Automated Detection and Classification of Oral Lesions using Deep Learning for Early Detection of Oral Cancer	2020	Roshan Alex Welikala , Paolo Remagnino , Jian Han Lim, Chee Seng Chan, Senthilmani Rajendran , Thomas George Kallarakkal , Rosnah Binti Zain4,, Ruwan Duminda Jayasinghe , Jyotsna Rimal , Alexander Ross Kerr.	The project used a deep learning approach called Faster R-CNN for object detection. It involved two main stages: the region proposal network (RPN) and the detection network. The RPN generated potential object locations in the image, while the detection network classified these locations and refined the bounding box coordinates. The model used a base convolutional neural network (CNN) to extract features from the input image.	The research gap lies in the need for a larger and more consistent dataset to improve the model's ability to identify complex patterns and generalize effectively.	Based on the given F1 scores and assuming equal weight for each task, the estimated accuracy of the project is approxima tely 68.91%

4. Early Diagnosis of Oral Cancer Using Image Processing and Artificial Intelligence	2024	Eman Shawky Mira*1 , Ahmed M. Saaduddin Sapri 2 , Rowaa F. Aljehanı3 , Bayan S. Jambı4 , Taseer Bashir5 , El-Sayed M. El Kenawy6 , Mohamed Saber	The study used smartphones and a clever method to diagnose oral cancer. They took pictures of lesions in the mouth using the phone's camera app with a special grid feature to keep things centered. These pictures were then sent to a computer for analysis. To deal with differences in picture quality, they came up with a way to make all the images more consistent. They also created a smart computer program using deep learning to diagnose oral cancer. When tested, it showed really good results in spotting the disease accurately. Overall, the study focused on taking clear mouth pictures, fixing picture differences, and using smart computer programs for oral cancer diagnosis.	Study only considered five categories for evaluation, and many forms of oral disease, such as oral thrush, were not included. Therefore, additional validation on other kinds of oral diseases and multiple smartphone cameras is necessary to thoroughly define the performance features of the AI diagnosis method.	The accuracy of the deep learning network in assessing oral cancer diagnosis was 84.3%.

Yang et al. (2023) demonstrate the effectiveness of deep learning in accurately identifying oral cancer stages using OCT images, highlighting its superiority over traditional machine learning approaches. Similarly, Tanriver et al. (2021) proposed a computer vision-based model for detecting oral cancer, emphasizing its potential as a real-time, low-cost, and non-invasive tool for early detection of oral potentially malignant disorders (OPMD) and carcinoma.

Mekala et al. (2022) and Anitha et al. (2022) further emphasize the importance of neural network-based approaches in enabling low-cost and early diagnosis of oral lesions, particularly in resource-constrained settings. Both studies advocate for the development of comprehensive libraries of well-annotated oral lesions to enhance detection accuracy.

Perumal and Manohar (2022) discuss the potential of deep machine learning techniques in aiding precision medicine for oral squamous cell carcinoma (OSCC), emphasizing the importance of early detection for improved prognosis. They highlight the role of deep learning in enhancing diagnosis, image classification, segmentation, and treatment planning for OSCC.

METHODOLOGY

In our methodology, we use CNNs, which are highly effective for recognizing images, to automatically detect oral cancer in medical images. This section aims to explain how we set up, trained, and assessed the CNN model for this purpose. In this we have also explained how we collected data, including getting and preparing oral cancer images.

Additionally, we describe our CNN model's design, discuss how we trained it, and explain the metrics we used to measure its performance.

Data Collection:

For the data collection phase of our study we acquired a comprehensive dataset comprising images specifically focused on oral cancer. This dataset was sourced from Kaggle. The images within this dataset depict rich and diverse set of samples for training and evaluating our CNN model. To guarantee quality and diversity, strict selection criteria were applied during dataset curation. This meticulous approach ensures our model is trained on a broad and representative range of oral cancer images, enhancing its precision and reliability in detecting and classifying oral cancer cases.

Preprocessing steps:

Resizing: Images in a dataset may come in different sizes. Resizing them to a standard size ensures consistency and makes them suitable for processing by the CNN.

Normalization: This involves scaling the pixel values of the images to a common range, typically between 0 and 1. Normalization helps in reducing the effects of lighting variations and makes training more stable.

Grayscale Conversion: Converting color images to grayscale can simplify processing, especially if color is not relevant to the task. It reduces computational complexity and can improve training speed.

Noise Reduction: Removing noise from images can enhance the signal-to-noise ratio and improve the network's ability to extract meaningful features. Techniques like blurring or denoising filters can be used for this purpose.

Augmentation: Data augmentation techniques such as rotation, flipping, scaling, and cropping can artificially increase the diversity of the training data. This helps prevent overfitting and improves the generalization ability of the model.

Feature Extraction: Depending on the task, certain features may be extracted from the images before inputting them into the CNN. This can involve techniques like edge detection or histogram equalization to highlight important patterns.

CNN Architecture:

Convolutional Layer:

This layer applies filters (small matrices) to input data, extracting features like edges, textures, and patterns. Each filter scans across the input data, performing mathematical operations to detect specific features.

Activation Function:

After convolution, an activation function like ReLU (Rectified Linear Unit) is applied to introduce non-linearity into the network. This helps the network learn complex patterns and relationships in the data.

Pooling Layer:

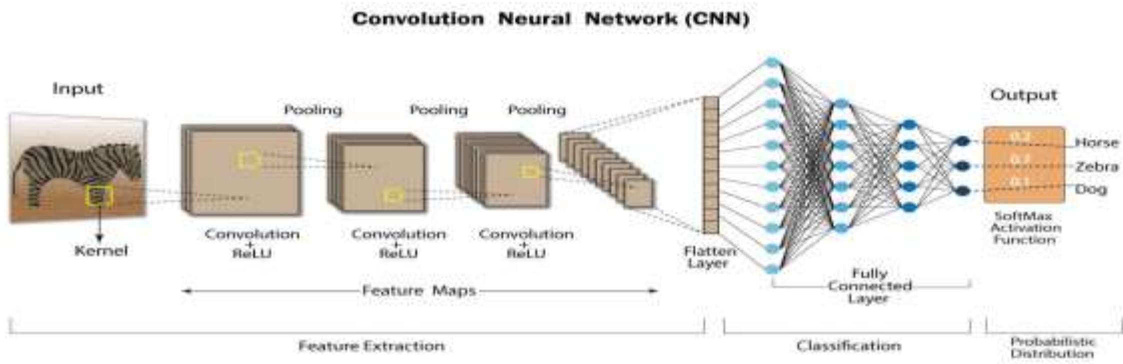
Pooling reduces the spatial dimensions of the feature maps generated by the convolutional layers. It does this by down sampling the feature maps, retaining only the most important information.

Flattening:

Flattening converts the multi-dimensional feature maps into a one-dimensional vector. This prepares the data for input into the fully connected layers.

Fully Connected (Dense) Layer:

In this layer, every neuron is connected to every neuron in the previous and subsequent layers. This allows the network to learn complex relationships between features and make predictions based on these relationships.



CNN Architecture

Output Layer:

The output layer produces the final predictions of the model. For classification tasks, it typically uses an activation function like softmax to convert raw scores into probabilities for each class.

These steps, working together, enable CNNs to automatically learn hierarchical representations of features from raw input data and make predictions based on these learned features.

A. Training Procedure

Data Collection: The first step in training an image recognition model is gathering a large dataset of images. This dataset needs to be diverse and representative of the types of images the model will encounter in the real world. It should include various categories and variations within those categories.

Data Preprocessing: Before training, the images in the dataset usually undergo preprocessing. This can involve tasks such as resizing images to a standard size, normalizing pixel values, and augmenting the dataset with transformations like rotations, flips, and crops. Data augmentation helps to increase the diversity of the training data and improve the model's generalization ability.

Model Selection: Next, you choose the architecture of the neural network that will serve as the image recognition model. Convolutional Neural Networks (CNNs) are commonly used for image recognition tasks due to their ability to effectively capture spatial hierarchies in images.

Model Initialization: The neural network model is initialized with random weights. These weights will be updated during the training process as the model learns from the training data.

Training Process:

I. Forward Pass: During each iteration of training, a batch of images is fed forward through the network. The network computes the predicted outputs (class probabilities) for each image in the batch.

II. Loss Computation: The predicted outputs are compared to the actual labels (ground truth) using a loss function such as cross-entropy loss. This computes a measure of the difference between the predicted and actual outputs. III. Backpropagation: The loss is backpropagated through the network, and gradients are computed with respect to the model's parameters (weights). This tells us how each weight should be adjusted to reduce the loss. IV.Parameter Update: The weights of the model are updated using optimization algorithms like stochastic gradient descent (SGD) or its variants (e.g., Adam). These updates are made to minimize the loss function. V. Iteration: The process of forward pass, loss computation, backpropagation, and parameter update is repeated for multiple iterations (epochs) over the entire dataset. Each iteration helps the model to learn better representations of the input data.

VI. Validation: Throughout the training process, a separate validation dataset is used to evaluate the model's performance on data it hasn't seen before. This helps to monitor the model's generalization ability and detect overfitting.
VII .Hyperparameter Tuning: Various hyperparameters, such as learning rate, batch size, and network architecture, may

need to be tuned to optimize the model's performance on the validation dataset.

VIII. Evaluation: Once training is complete, the final trained model is evaluated on a separate test dataset to assess its performance in real-world scenarios.

IX. Deployment: The trained model can then be deployed to make predictions on new, unseen images in production environments.

The training process may involve significant computational resources, especially for large datasets and complex models. Techniques like transfer learning can also be employed to leverage pre-trained models and fine-tune them for specific tasks, which can reduce the amount of training required.

B. Testing Procedure

Test Dataset:

Similar to the training process, you need a separate dataset for testing the trained model. This test dataset should be distinct from the training and validation datasets and should represent real-world scenarios that the model will encounter.
Data Preprocessing:

Like in training, the test images may undergo preprocessing steps such as resizing, normalization, and augmentation if necessary. However, it's important to ensure that the preprocessing steps applied to the test data are consistent with those applied during training.

Model Evaluation:

1.Forward Pass: The preprocessed test images are fed forward through the trained model, and predictions (class probabilities) are obtained for each image.
2.Prediction Analysis: The model's predictions are compared with the ground truth labels for the test images. Metrics such as accuracy, precision are commonly used to evaluate the model's performance.
3.Performance Assessment: The performance of the model is assessed based on these evaluation metrics. This helps to understand how well the model generalizes to unseen data and whether it exhibits any biases or errors.

C. Accuracy Achieved for Training and Testing Data

In this training the dataset takes time to train , while training the data , data is preprocessed and noises are removed from the images for further better processing and testing of images.

$$\text{Accuracy} = \frac{\text{No. of Correct predictions}}{\text{Total number of predictions}}$$

Below given image is the percentage of training and testing accuracy achieved.

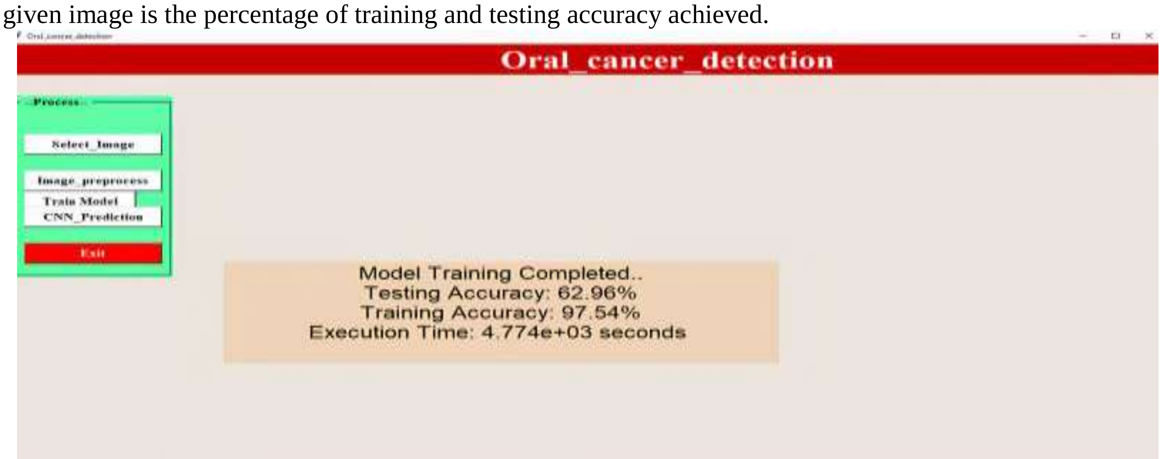


Fig. I Accuracy

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D. Implementation

After training the data,this data can be useful for detection purpose .

1.This is the main GUI of our project implementation.It contains three buttons for image processing and prediction.

Fig . II GUI of Project

Step 1: Select image from trained dataset.

Fig. III Image Selection Process

Step 2: Apply image preprocessing step by clicking image preprocess button.This converts given into gray scale form and then into binary form for further CNN prediction.

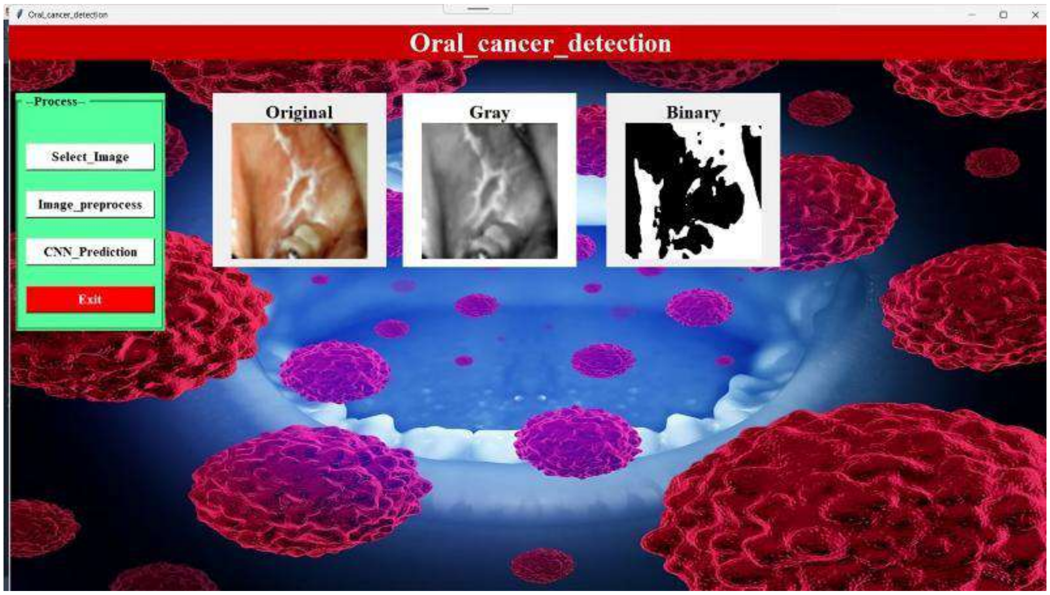

Fig. IV Apply Preproceesing Techniques

Step 3: Apply CNN prediction on it by clicking CNN prediction button. This gives an output as if the given image is of oral cancer or other types of it or just a normal image.

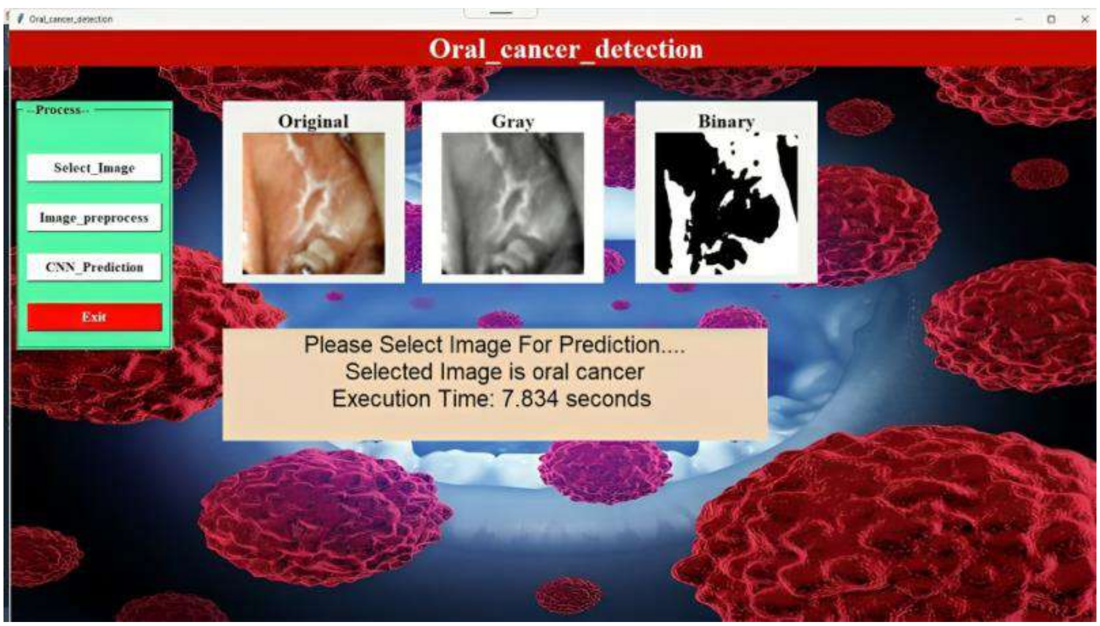

Fig. V CNN Prediction Result

At last the prediction gives an output as if it is a oral cancer or its type or just a normal image.

RESULT

The below graph shows our oral cancer detection system getting better at its job over time. Both training and testing accuracies increase at first, which means the system is learning well. Even though testing accuracy levels off, training accuracy keeps improving. This suggests our system is becoming good at recognizing oral cancer patterns. So, with more training, it could become even more accurate at detecting oral cancer.

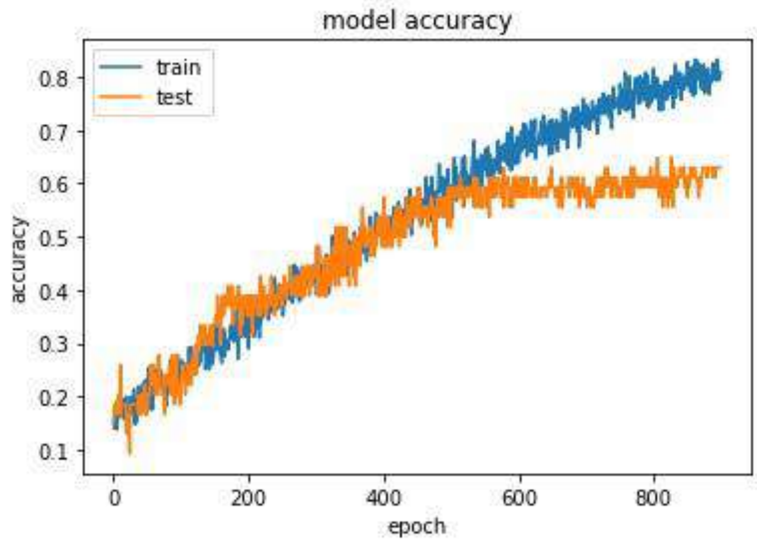

Fig VI Accuracy Graph

The below graph shows that our oral cancer detection system is improving. As training progresses, the loss decreases steadily, indicating that the model is getting better at its job. Though there's a slight increase in loss during testing after a certain point, overall, the trend is positive. This suggests that our system is learning well and becoming more effective at detecting oral cancer.

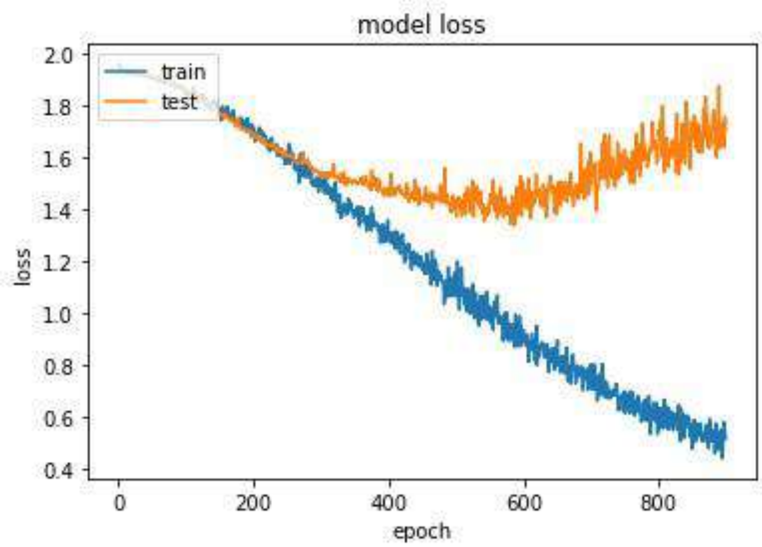

Fig VII . Loss Model Graph

CONCLUSION

Our project on automated oral cancer detection is a big step towards healthcare. We've created a smart system that can find signs of oral cancer accurately and without causing any discomfort to patients. This could really help doctors catch cancer early, improve how healthcare works, and ease the pressure on medical services. It's important to keep testing and using this technology to make sure it helps as many people as possible.

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REFERENCES

[1]. Zihan Yang,Hongming Pan,Jianwei Shang,Jun Zhangand Yanmei Liang, "Deep-Learning-Based AutomatedIdentification and Visualization of Oral Cancer inOptical Coherence Tomography Images" ,2023.

[2]. Gizem Tanriver, Merva Soluk Tekkesin, Onur Ergen ,"Automated Detection and Classification of OralLesions Using Deep Learning to Detect Oral PotentiallyMalignant Disorders " , 2021.

[3]. Dr. G. Kavya,K. Mekala Devi,R.Ashwini,M.Priscilla,R.S.Vijayashanthi , "ORALCANCER DETECTION USING CNN",2022.

[4]. Rasheed Omobolaji Alabi,Alhadi Almangush,Mohammed Elmusrati,Antti A. Mäkitie , "Deep MachineLearning for Oral Cancer: From Precise Diagnosis toPrecision Medicine " , 2022.

[5]. C. ANITHA,S. SASIKUMAR , "Oral Cancer Detection byCNN" , 2022.

[6]. Qiuyun Fua, Yehansen Chene,Zhihang LiKaixiong Lia,Haixiao Zouh, Yong Songi, gkun Wang,Xiqian Wangk,Yufan Wangl, Jianying Lium, Hui Liun, Sulin Cheno,Ruibin Chenp, Man Zhangd,Jingjing Zhaoq, JunboXiangc, Bing Liua, Jun Jiaa, Hanjiang Wur, Yifang Zhaoa,Lin Wane,Xuepeng Xiong , "A deep learning algorithmfor detection of oral cavity squamous cell carcinomafrom photographic images: A retrospective study",2020.

[7]. Takamichi Morikawa,Takahiko Shibahara,TakeshiNomura,Akira Katakura and Masayuki Takano , "NonInvasive Early Detection of Oral Cancers UsingFluorescence Visualization with Optical Instruments",2020.

[8]. Patil S, Sarode SC, Baeshen HA, Bhandi S, Raj AT, Sarode GS, et al. Bibliographic analysis of oral precancer and cancer research papers from Saudi Arabia. Asian Pac J Cancer Prev APJCP 2020;21:13–8.,2020

[9]. Ganly I, Hao Y, Rosenthal M, Wang H, Migliacci J, Huang B, et al. Oral microbiome in nonsmoker patients with oral cavity squamous cell carcinoma, defined by metagenomic shotgun sequencing. Cancers 2022;14. https://doi.org/10.3390/ cancers14246096.,2022

[10]. Herreros-Pomares A, Hervas D, Bagan-Debon L, Jantus-Lewintre E, Gimeno- Cardona C, Bagan J. On the oral microbiome of oral potentially malignant and malignant disorders: dysbiosis, loss of diversity, and pathogens enrichment. Int J Mol Sci 2023:24.

[11]. Søland TM, Bjerkli IH, Georgsen JB, Schreurs O, Jebsen P, Laurvik H, et al. Highrisk human papilloma virus was not detected in a Norwegian cohort of oral squamous cell carcinoma of the mobile tongue. Clin Exp Dent Res 2021;7:70–7. 2021.

[12]. Screening for oral cancerda perspective from the Global Oral Cancer Forum Paul M. Speight, BDS, FDSRCPS, FDSRCS (Eng), PhD, FRCPath,a Joel Epstein, DMD, MSD, FRCD(C), FDSRCS(Edin),b Omar Kujan, DDS, DipOPath, MSc, PhD,c Mark W. Lingen, DDS, PhD,d Toru Nagao, PhD, DMSc, DDS,e Kannan Ranganathan, MDS, MS, PhD, FIAOMP,f and Pablo Vargas, DDS, MSc, PhD, FRCPathg

[13]. Oral Cancer Screening: Past, Present, and Future S. Warnakulasuriya1 and A.R. Kerr2 .

[14]. Early Diagnosis of Oral Cancer Using Image Processing and Artificial Intelligence Eman Shawky Mira , Ahmed M. Saaduddin Sapri , Rowaa F. Aljehanı , Bayan S. Jambı , Taseer Bashir , El-Sayed M. El-Kenawy , Mohamed Saber.

[15]. Automated Classification of Oral Cancer Histopathology images using Convolutional Neural Network.Santisudha Panigrahi and Tripti Swarnkar,2019.