A Comparative Study on Tongue Tumor Detection and Classification Using Neuro Dynamic Ensemble Fusion Classifier

S. Preethi[1], K. Raju[2], Rajalakshmi D[3], P. Venkata Subba Reddy[3], Shaik Taher[3] and Sannapu Deepak[3]

[1]*Department of Information Technology, E. G. S. Pillay Engineering College, Nagapattinam, Tamil Nadu, India*
[2]*Department of Artificial Intelligence and Machine Learning, Rajalakshmi Engineering College, Chennai, Tamil Nadu, India*
[3]*Department of Computer Science and Engineering, R.M.D Engineering College, Chennai, Tamil Nadu, India*

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Abstract: Recently, the deep learning technique plays a vital role in health care industries to classify and diagnose any disease at early stage. By applying deep learning algorithms, the diseases such as heart disease, brain tumor, lung disorder, and several other deadly diseases has been early diagnosed. This promising technique endlessly extends its viability in detecting oral cancer. This life threating tumor can forms on any region of the mouth namely uvula, tonsil, gum, palate and cheeks. As mouth has been the crucial part in our body, because it performing functions such as eating, sleeping and breathing. Hence, early detection and diagnosing of oral cancer is mandatory. If it is not treated, this disease endangers the life of humans. Earlier the traditional convolutional neural networks were used for diagnosing oral cancer. But the advancement of information technology brings development in neural networks. This study proposes a novel Neuro dynamic ensemble fusion (NDEF) classifier to enhance the detection of oral cancer at earliest. The proposed model is tested on the publically accessible oral cancer dataset and comparing its performance with other classifiers including a hybrid RCNN and ResNet—50, VGG16, and U-Net. This proposed classifier exhibits higher accuracy of 96.27%, precision and recall of 96% and 94%, respectively. The NDEF has obtained promising results and accurately detected the affected regions as well.

1 INTRODUCTION

The term “cancer” is known as a disease where the abnormal body cells dissect enormously and damage the tissues of the whole body. About 200 more types of cancers have been discovered. The most frequently occurring cancers take place in the breast, lungs, skin, stomach, liver and tongue. According to the World Health Organization (WHO), oral cancer is one of the most dominant and widely spreading types of cancer and its mortality rates are also high in several countries notably in South Asia. Usage of tobacco, consuming heavy amounts of alcohol, and HPV infection with some specific genetic factor cause the tongue tumor in which the cancerous cells dissociate from the tumor and spread to the other parts of the body especially inside the mouth, head, neck, in the areas of lungs and the areas which are close to the lymph nodes. In India, nearly 52,000 people die of tongue tumor per year. So, detecting and curing it in its early stage is mandatory which saves thousands of people from its threat.

In human life, the Artificial Intelligence (AI) techniques play a vital role which helping people being endangered. Deep learning is one among them that has a significant impact on detecting tongue tumor. Some of the earliest detection methods for tongue tumor were, (K. Nakanura et al., 2012) used Raman Spectroscopy-based system for detecting oral cancer which is non-invasive and reduses the risk of discomfort but failed to produce larger number of datasets and could be more expensive. And then, (S. Wang et al., 2017) detected tongue tumor with the help of CNN (Convolutional Neural Network) based detection with simple architecture along with the robust feature extraction it couldn’t provide a larger number of datasets. Following this, (y. zhang et al., 2018) used Auto encoder-based detection which provided unsupervised learning but only had limited features. Additionally, (S.S Iyer et al., 2019) used

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transfer learning-based detection which is an efficient training model but it ended up with a limited fine issue. The above researchers were some of the earliest detection of tongue tumor using the existing models. This study let us analyze how to recognize and classify tongue tumor with proper pre-processing filtering called Multi Scale Adaptive Filtering by image resizing, and denoising in addition to some of the feature extraction processes which is followed by the specific segmentation called Fractal Texture Mapping for Neurodegenerative Segmentation (FTM-NS) technique for depicting the affected areas. Finally, the process is classified using the classification model named as Neuro-Dynamic Ensemble Fusion to detect and eradicate the tumor in its early stage. This study also serves as a comparative analysis of existing and proposed tongue tumor detection techniques for better results.

2 RELATED WORKS

To utilize deep learning for detecting the abnormal growth of oral tissue (Welikala et al., 2021) applied an Artificial Neural Network (ANN) for the automated detection of oral lesions. This study promotes the early identification of oral lesions which can significantly reduce treatment costs and even prevent mortality rates. To classify the image, the ResNet-101 model was employed achieving an accuracy of 87.07%. Furthermore, the damaged tissues in the images were accurately identified with 78.3% of precision. Though the performance in identifying followed by classifying tongue tumours using DNN was demonstrated acceptably, several limitations were also noted, which include limited data set size inconsistent annotations lack of external validation restricted evaluation metrics followed by the absence of comparative analysis with limited clinical validation. (Nandita et al., 2022) employed both deep learning and machine learning techniques, which promote the identification of tongue tumours. In this study, a Convolutional Neural Network (CNN) with 43 deep layers was engaged to predict the data. This results in detecting CT scan images with high accuracy which is also effectively stimulating malignant oral lesions with utmost precision. AI has become apparent in the diagnosis of several diseases, including cancer. To identify the tongue lesions, (Panigrahi et al., 2022) employed histopathological images. This study assessed 6 widely used algorithms called Support Vector Machine (SVM), Random Forest, Neural Network, Simple Bayes, Decision tree and K- nearest neighbor (KNN) which are the most relevant methods in classifying oral lessons. Additionally, the study admitted that the neural network algorithm achieved its reasonable accuracy of 90.4% with satisfactory potential in diagnosing the disease. (Singh et al., 2022) introduced an innovative intelligent computing framework for deducting tongue tumours. He evaluated the strategy with the help of the disease imaging data. This concluded in revealing the tumor in their early stage. To distinguish healthy tissue from cancerous tissue (Jeng et al., 2022) utilised Raman spectroscopy through specific subsite analysis. This focused on the tongue, gingival and buccal mucosa. The classification of healthy and cancerous tissues was successful by employing Linear Discriminant Analysis (LDA) followed by Quadratic Discriminate Analysis in cooperation with Principle Quality Analysis (PQA). Principally, Raman's Spectroscopy highlighted the potential in detecting oral cancer by finding that the proteins, amino acids and beta carotene served as consequent biomolecular markers to get rid of cancer. (Sahu et al., 2023) achieved a sensitivity of 64% and specificity of 80% with the application of the Principle Component Liner Discriminate Analysis Mode which examined the potential of serum Raman Spectroscopy in diagnosing tongue tumor. Though they tend to have some limitations, they lead to optimal performance in spectral data classification. Despite this, deep learning models enable automatic feature extraction from raw data to an end-to-end learning approach. Hence these deep learning AI models have an optimistic perspective in improving the accuracy of tumor classification.

3 METHODOLOGY

This section provides a detailed explanation of the steps followed in proposed technique which includes dataset collection, pre-processing, segmentation and classification.

3.1 Dataset Collection

The current study utilizes the oral cancer images acquired from a publicly available oral cancer data set. The images of the oral cancer obtained from the database are in the JPEG format, which is with a specific resolution of 256 × 256 pixels. The obtained dataset holds the collection of tongue Figure 1 which are grouped into two categories, namely cancerous and non-cancerous images. Furthermore, the images in the dataset comprise 500 sets of oral cancer images and 450 sets of non-cancer oral images, which are being compiled that can be used for various medical visualization in the detection and therapeutic treatment of oral cancer earlier.

Figure 1: Non-cancerous and cancerous tongue.

3.2 Pre-Processing

In this study, the images will be compiled from classified reports, which offer significant data for better study. Moreover, the images which are obtained from the specific source have some complications which we have to work on like the quality of the image, and its structure followed by some denoising process. Though some of the images are quite clear and well-organized others may be composed by the presence of noise which makes the study to be decreased in its accuracy. To overcome the issue, some of the preprocessing techniques are essential to enhance the quality of the image, ultimately promoting the betterment of the proposed study. For enhancing the image quality effectively, multi scale adaptive filtering serves as a crucial pre-processing step in tongue tumor detection.

Denoising: It is very difficult to detect the tongue tumor accurately from the tissue surrounding the tumor. It's been more complicated when the image quality is compromised by noise or even lightning. This is effectively eradicated with the help of the multiple scales adaptive efficiently and reducing the noise by preserving some crucial details, including the edges of the tumor and contours, therefore making tumor identification much easier. At first, the noisy images cannot be detected accurately. So, the adaptive filter helps in locating the edges of the images which are composed of noises. Next, the images which are comprised of noises are decomposed with the wavelets. Then the edges are located with the adaptive filters. The edges and the contours were detected at multiple scales. Furthermore, the adaptive filters store the details of the images even after removing the noises. At each selected scale the process of filtering is applied to the image. By analysing and adjusting its guidelines based on the texture, contrast and intensity in that particular region, the filter is being operated. After the filtering has been done in multiple scales, the scale allows the preservation of the edges of small tumours and the structure of the borders. The processed final image is then claimed and detailed with enhanced features making it suitable for further processing. This Multi-scale adaptive filtering process ensures the improvement in tumor detection's accuracy, better edge detection, and adaptability rather to the other filters. Finally, multi-scale adaptive filtering makes the tumor detection more reliable by playing a crucial role in improving image quality.

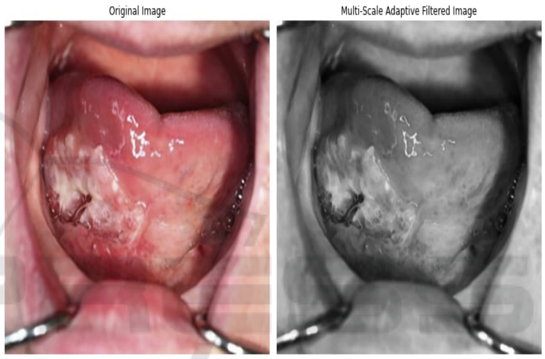

Figure 2: Original and the filtered image using Multi-scale adaptive filter.

To remove noise from an image while keeping important details like edges, a technique called Multi-scale Adaptive Filtering is used. This method involves applying filters at different scales to the image. Each scale reduces noise in a specific way. This process Figure 2 Shows the Original and the filtered image using Multi-scale adaptive filter. can be broken down into mathematical steps to achieve effective denoising. The general mathematical equation for the denoising process using Multi-scale Adaptive filter is given below.

Let $I(x,y)$ be the pixel coordinates of the noisy image. Initially, the image is decomposed into Multiple Scales.

Let $I_s(x,y)$ represent the image at the s'th scale, where $s = 1,2,\dots, S$ and S is the number of scales. At scale s, the adaptive filter F_s is applied to the image $I_s(x,y)$ yielding the filtered image $\hat{I}_s(x,y)$: $\hat{I}_s(x,y) = F_s(I_s(x,y),\sigma_s)$

Where σ_s represent the noise variance that depends on the scale. The images at different scales are then combined to produce the final denoised output. This is given by, $\hat{I}(x,y) = \sum_{s=1}^{S} w_s \hat{I}_s(x,y)$

where ws is the weight assigned to each scale that depends on factors like the scale or the effectiveness of the denoising at that scale. Finally, the denoised image $\hat{I}(x,y)$ is used as the input for the detection of tongue tumor. Hence this ensures the reduction of noise effectively at multiple scales which allows for better tongue tumor detection.

3.3 Segmentation

After the Multi-scale adaptive filtering, the enhanced image is now ready for the tumor segmentation. Fractal Texture Mapping for Neurodegenerative Segmentation (FTM-NS) works by segmenting the texture of the images which consist tumor. The affected patterns may be fractal which remains the same across different scales. Hence, fractal texture mapping helps in segmenting the tumor of neurodegenerative diseases, which exhibit complex structures at different scales. It highlights the irregularities in tissue patterns caused by tumor by mapping these fractal characteristics. Firstly, it identifies the affected areas. The affected areas may have irregular patterns. The fractal method helps in analyzing the irregularities and detects the changes. Next, the detected changes of the neurodegenerative diseases are mapped, which helps in differentiating the tumorous and the non-tumorous tongue. Finally, the segmentation process takes place by locating the affected areas at various scales. Thus, the affected tissues with complex structures are detected by fractal geometry, which results in mapping the changes in the texture for more accurate segmentation in neurodegenerative diseases. This method enables the exact segmentation and the reduction of abnormalities accurately. For a better understanding, the tumor in a tongue is segmented and the image is projected below Figure 3.

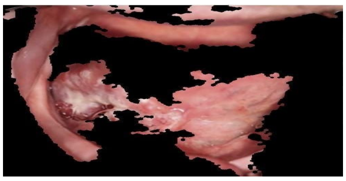

Figure 3: Segmented tongue using FTM-NS.

3.4 Classification

Neuro-Dynamic Ensemble Fusion (NDEF) classification is one of the best classifiers for detecting tongue tumor. It combines various tumor detecting techniques to classify the tumor in the tongue with an increased amount of accuracy. It works by involving the neural networks, where the information is being processed. These neural networks can handle the complex patterns which are in the acquired images. Then the models which depend on one another are ensembled. Then those ensemble models work together resulting in classifying the tumor with accurate prediction. Finally, the tumor are classified after sorting the data in the medical images. In brief, this proposed NDEF combines different neural networks with various models and fuses the techniques of the models with the networks to classify the tongue tumor more accurately. Thus, the Neuro Dynamic Ensemble Fusion (NDEF) model results in excellent tongue tumor detection. It outperforms the existing models like RCNN, ResNet-50, VGG16, and U-Net. NDEF combines multiple algorithms which increases the accuracy and robustness. It adapts to complex patterns and features in medical imaging. This makes NDEF to be the most effective for tongue tumor detection. For the earliest detection and diagnosis, accurate detection of the disease is a must. Several deep learning models, including RCNN, ResNet-50, VGG16, and U-Net, are also being used for medical imaging. Each of the models has its strengths and weaknesses. This study also compares the performance of the existing models with the proposed Neuro Dynamic Ensemble Fusion (NDEF) model for enhanced tongue tumor detection.

RCNN is mainly used for the detection of objects. It works by using a CNN to classify every region and divide the images into regions of interest (RoIs). This process makes RCNN detect specific regions such as tumor and the affected areas effectively. Moreover, RCNN plays a significant role in detecting and segmenting the tumor within the image. Though it detects the tumor efficiently it also has some limitations. One of the major drawbacks is, that the speed of the image processing is extremely slow which further processing steps like, feature extraction, and classification. This also makes the RCNN perform very slowly in medical diagnostics. The next major drawback is, that RCNN requires a larger number of computational resources, particularly in handling huge medical images. This can’t be resolved making RCNN work slowly. Hence in the detection of tongue tumor, RCNN supports detecting the tumor regions effectively. However, its slow processing speed limits its work in the earliest disease diagnostics, as the fastest detection and diagnosis are very important.

ResNet-50 is also a deep learning, convolution neural network model. It uses residual connections which makes deeper networks. It is very significant in detecting even a tumor with minor characteristics which is very effective in medical image analysis. Its enhanced architecture helps us to analyze the tumor which has irregular features and patterns. It has residual connections which prevent degradation. This makes it applicable to deeper networks. ResNet-50 is known for its larger number of datasets making it beneficial for analyzing medical images. However, this classifier too has some limitations. As the model is very large, the highest memory storage is required. The next major drawback is, that to gain the highest accuracy in tongue tumor detection; the model has to be tuned finely along with the labelled data.

VGG16 is also a deep learning-based convolution neural network. It has enhanced features which are well known for its simple architecture and peculiar structure. The model has 16 layers, with 3x3 filters which can be applied through all the layers along with small receptive fields. This makes the medical diagnosis very easy as it classifies the image accurately which promotes the model to be popular among the researchers. Furthermore, its unique structure helps it to understand and implement the image classification process very easily. The 16 layers in the model allow for projecting even the complicated details in the image which makes the tumor detection very easier. Though it works very efficiently, this too has some limitations. As the structure is deep, the model requires the highest amount of memory storage and increases the computational costs which results in overfitting. Additionally, the model gives only a limited number of datasets. However, VGG16 is very useful in classifying the tongue tumor but the model may not work very efficiently due to its overfitting property and limited number of datasets which results in giving poor quality data.

U-Net is a popular architecture which used as a deep learning model for semantic segmentation mainly in medical image analysis. It works with the help of an encoder-decoder architecture which has skip connections that help preserve tumor based information. This feature makes U-Net perform accurately in segmenting and classifying the images. It works well not only in classifying the images but also in segmenting the tumor edges perfectly in the detection of tongue tumor. U-Net models are trained by using a minimum number of datasets with limited data. Moreover, U-Net has also struggled with some limitations. As it is very good at segmenting the images, it couldn't perform well in classifying the images. As a result, U-Net requires additional classification steps in the detection of tongue tumor to make the treatment quick and easier.

Neuro-Dynamic Ensemble Fusion (NDEF) classification is one of the best classifiers for detecting tongue tumor. It combines various tumor-detecting techniques to classify the tumor in the tongue with an increased amount of accuracy. It works by combining multiple neural networks to improve classification accuracy. Based on the features obtained from the tumor, their learning patterns and the data that is imported into the image, the neural networks operate and update the classification efficiently. It combines various types of classifiers, which are from different neural networks to generate a final decision by improving the robustness. The combination of the classifiers helps in predicting the image data from different models which results in producing the accurate classification.

The following Figure 4 grouped below shows the classification of the tumor in the tongue and the non-tumorous tongue for more clarification.

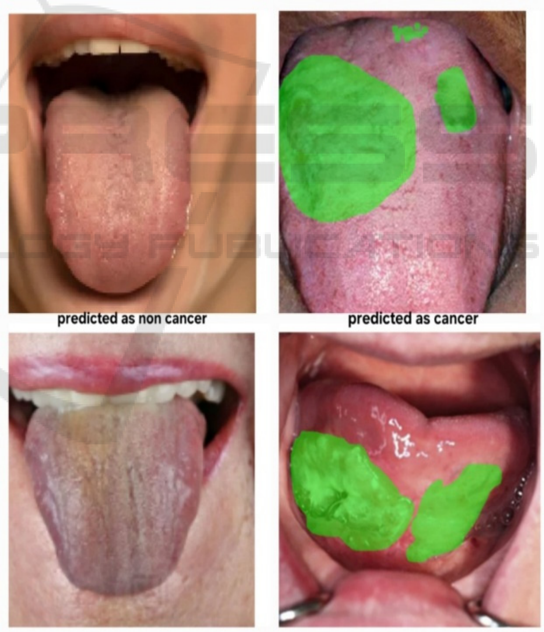

Figure 4: Classification result.

4 RESULT & DISCUSSION

The Proposed system was validated using the publically available data set which contains Images of the oral cancer with 256 x 256 pixels that can be used for medical visualization with correct resolution. For enhancing the image quality, denoising and filtering is done by using the Multi-scale Adaptive Filter and the proper image is obtained which makes it suitable for the further processing like segmentation. The tumor affected area is segmented perfectly with the help of Fractal Texture Mapping Neurodegenerative Segmentation. It highlights the irregularities in tissue patterns caused by tumours by mapping these certain characteristics. Finally, in classification, the existing models like RCNN, ResNet50, VGG16 and U-Net are compared with NDEF's classification model and concluded that the highest accuracy and reliability is most effective in tongue tumor deduction is acquired only by using NDEF classification model.

Further the evaluation metrics namely accuracy, precision-recall, are widely utilised in the field of image classification to describe the model's performance.

The proposed classifier has achieved the accuracy of 96.27% more than the other existing models like RCNN+ResNet50 which have 93.22%, VGG16 which has 90.81% and UNet which has 88.04% of accuracy which is shown in Figure 5.

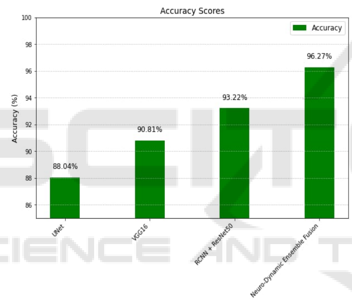

Figure 5: Accuracy comparison.

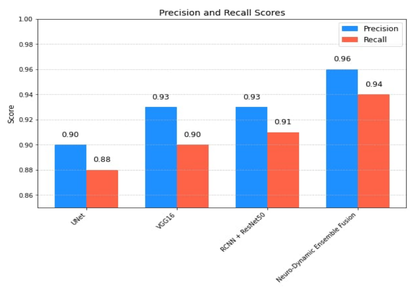

Figure 6: Precision-Recall comparison.

Its effectiveness is also been calculated by the precision and recall scores in which the proposed model has achieved the highest precision of 0.96 and recall score of 0.94 than the existing model which are discussed in the Figure 6. The training and testing accuracy obtained by the proposed classifier is depicted in Figure 7.

Figure 7: Validating the Training and Testing accuracy.

Here, the proposed model has the highest training and testing accuracy of about 96.27%

For the further enhancement of the proposed study, the works of different authors using the existing methods are also compared. From the proposed NDEF technique, it is known that the technique has overcome all other methods in detecting the tongue tumor with the highest accuracy of 96.27%. In (P. Kalaivani, 2022) the technique uses the Gabor Filter for increasing image quality along with the K-Means Clustering segmentation for detecting affected areas which has an accuracy of 94%. Despite, this the technique used in (L. Li et al., 2022) that employs Gabor, Sobel, and Median Filters, for pre-processing and Thresholding, K-Means Clustering, and Watershed Transform methods for segmentation achieves an accuracy of 93%. In the techniques (W. Wang et al., 2023) and (J. Heo, 2022) the image quality is done by using Multi-Resolution Analysis Filters and Gaussian filter, Median filter, CLAHE along with the region-based segmentation and Mask R-CNN& U-Net segmentation models in depicting the tumor areas resulting in the accuracies of 82% and 78.6%, respectively. Technique (T. Thakuria, 2022) achieves the accuracy of 89.47% by using Gaussian, Median, CLAHE, Wiener, and Anisotropic Diffusion Filter and by using FCN, SegNet, and DeepLab segmenting models. Finally, NDEF has its significant combination of Multi-scale Adaptive Filter along with FTM-NS segmentation technique over all other techniques, which results in the highest position as the most effective method for tongue tumor detection. Table 1 Shows the Comparing the other existing technique with the proposed technique.

Table 1: Comparing the other existing technique with the proposed technique.

Author Name	Dataset	Filter	Segmentation	Accuracy
W. Wang et al.,	Oral cancer dataset	Multi-Resolution Analysis Filters	Region based segmentation	82%
P. Kalaivani	Oral Histopathology Dataset	Gabor Filter	K-Means Clustering	94%
L. Li et al.,	Oral Cancer Dataset	Gabor, sobel & median filters	Thresholding, K-Means clustering & Watershed transform	93%
J. Heo	TCEED (Tongue Cancer Endoscopic Dataset)	Gaussian filter, Median filter& CLAHE	Mask R-CNN& U-Net	78.6%
T. Thakuria	Oral Cancer Dataset	Gaussian, Median, CLAHE, Wiener and Anisotropic diffusion filter	FCN, SegNet & DeepLab	89.47%
Proposed NDEF	Oral Cancer Dataset	Multi-scale Adaptive Filter	FTM-NS	96.27%

5 CONCLUSIONS

The experimental results of the proposed Neuro Dynamic Ensemble Fusion mechanism have achieved its maximum accuracy. While comparing the proposed with the other classification models, the NDEF approach achieves accurate tumor detection even at low resolutions. The use of Fractal Texture Mapping for neurodegenerative segmentation enhances the exact tumor-affected regions by its effective segmenting technique and the Multi-scale Adaptive Filtering helps in eliminating the impurities in the images including the edges. Thus, the model helps the information to be preserved on the original image. The increased prediction level trains the model to extract the essential features in the feature extraction technique. As a result, the model achieves an overall accuracy of 96.27%, which serves as the perfect replacer of other classification models. The proposed model's effectiveness is proved by the evaluation metrics such as precision and recall. In summary, the proposed model offers efficient and accurate tongue tumor detection, with a large number of datasets and decreased detection time. Thus, it serves as the best alternative approach to any other models for effective tongue tumor detection.

REFERENCES

K. Nakamura, "Raman spectroscopy for detecting oral cancer," Diagnostics, vol. 12, no. 12, pp. 2896, 2012.

S. Wang et al., "Detection of tongue tumor using convolutional neural network (CNN)," *Computer Methods and Programs in Biomedicine*, vol. 145, pp. 73-82, 2017, doi: 10.1016/j.cmpb.2017.04.011.

Y. Zhang et al., "Automatic detection of tongue tumor using auto encoder and support vector machine," *IEEE Access,* vol. 6, pp. 38601-38609, 2018, doi: 10.1109/ACCESS.2018.2854823.

S. S. Iyer et al., "Transfer learning-based tongue tumor detection using deep neural networks," *IEEE Access*, vol. 7, pp. 103941-103953, 2019. doi: 10.1109/ACCESS.2019.2931953

X. Cai, "Breast cancer diagnosis by convolutional neural network and advanced thermal exchange optimization algorithm," *Computational Mathematics and Methods in Medicine,* vol. 2021, 2021.

Nanditha, B., Geetha Kiran, A. Sanathkumar, M. P., "Oral cancer detection using machine learning and deep learning techniques," *International Journal of Current Research and Review*, vol. 14, no. 01, pp. 64, 2022.

S. Panigrahi, B. S. Nanda, and T. Swarnkar, "Comparative analysis of machine learning algorithms for histopathological images of oral cancer," in *Advances in Distributed Computing and Machine Learning, Springer,* 2022, pp. 318-327.

A. Singh, A. Sahu, and S. Verma, "Computer intelligence in detection of malignant or premalignant oral lesions: The story so far," *Computer Intelligence in Oncology*, vol. 1016, pp. 187-200, 2022.

C.I. Faur et al., "Raman spectroscopy in oral cavity and oropharyngeal cancer: a systematic review," *International Journal of Oral and Maxillofacial Surgery*, vol., pp., 2022.

"Deep multi-feature fusion residual network for oral squamous cell carcinoma classification and its intelligent system using Raman spectroscopy," *Biomedical Signal Processing and Control*, vol., pp., 2023.

W. Wang, Y. Liu, and J. Wu, "Early diagnosis of oral cancer using a hybrid arrangement of deep belief network and combined group teaching algorithm," *Scientific Reports*, vol. 13, pp. 22073, 2023.

P. Kalaivani, "Oral cancer detection using deep learning," *Journal of Intelligent Information Systems*, vol. 60, no. 2, pp. 347-362, 2022. doi: 10.1007/s10844-021-00761-5.

L. Li, C. Pu, J. Tao, L. Zhu, S. Hu, B. Qiao, L. Xing, B. Wei, C. Shi, P. Chen, and H. Zhang, "Development of an oral cancer detection system through deep learning," Computers in Biology and Medicine, vol. 142, pp. 105512, 2022.
doi: 10.1016/j.compbiomed.2022.105512.

J. Heo, "Deep Learning Model for Tongue Cancer Diagnosis Using Endoscopic Images," *Journal of Clinical Medicine, vol. 11, no. 11, pp. 3024, 2022. doi: 10.3390/jcm11113024.*

T. Thakuria, "Deep learning for early diagnosis of oral cancer via smartphone and DSLR image analysis: A systematic review," Journal of Oral Pathology & Medicine, vol. 51, no. 9, pp. 641-653, 2022. doi: 10.1111/jop.13441.

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