AUTOMATED LION OPTIMIZATION ALGORITHM WITH DEEP TRANSFER LEARNING BASED ORAL CANCER DETECTION AND CLASSIFICATION MODEL

Reference NO. IJME 2525, DOI: 10.5750/sijme.v167iA2(S).2525

Sathishkumar R*, Research Scholar, Department of Computer Science and Engineering, Annamalai University, Annamalai Nagar, 608002, Chidambaram, Tamil Nadu, India and **Govindarajan M,** Associate Professor, Department of Computer Science and Engineering, Annamalai University, Annamalai Nagar, 608002, Chidambaram, Tamil Nadu, India

*Corresponding author: Sathishkumar R (Email): sathishmail26@gmail.com

KEY DATES: Submission date: 10.09.2024; Final acceptance date: 23.03.2025; Published date: 30.04.2025

SUMMARY

Oral cancer (OC) recognition involves leveraging innovative technologies like imaging models and machine learning (ML) techniques to analyze oral cavity anomalies, helping in the initial analysis and enhancing treatment results. These new methods contribute to appropriate intervention and the probable for improved existence rates in individuals in danger of oral cancer. The normal analysis of oral cancer is the microscopic study of specimens detached especially over incisional biopsies of oral mucosa through a clinical spotted suspicious lesion. The use of deep learning (DL) methods is effective in many kinds of cancer; but, a restricted research study has been completed utilizing histopathological OSCC images. Unlike conventional ML, which needs physical feature removal and reflects area expertise, DL can mechanically remove features with an alteration from hand-designed to data-driven features. Despite the customary medical techniques employed in oral classification, automatic models dependent upon a DL framework display promising outcomes. Therefore, this article presents an automated lion optimization algorithm with a deep transfer learning-based oral cancer detection and classification (LOADL-OCDC) methodology. The main intention of the LOADL-OCDC technique is to recognize and categorize the occurrence of oral cancer into distinct classes. The LOADL-OCDC technique follows a multistage process. Initially, the LOADL-OCDC technique performs bilateral filtering-based noise elimination and CLAHE-based contrast improvement. Next, the EfficientNet model can be applied to learn complex and intrinsic feature patterns from the pre-processed images. In the presented LOADL-OCDC technique, the lion optimization algorithm (LOA) can be applied for fine-tuning the hyperparameters of the EfficientNet model. For cancer detection, the LOADL-OCDC technique applies a deep recurrent neural network (DRNN) system. A general experimental study is created to investigate the detection results of the LOADL-OCDC technique. The complete comparison study reported the supremacy of the LOADL-OCDC system in terms of different measures.

KEYWORDS: Oral cancer, Transfer learning, Lion optimization algorithm, Bilateral filtering, Histopathological image

1. INTRODUCTION

Currently, the rate of oral cancer (OC) especially OSCC is growing, and the primary cause behind this increase must be tobacco chewing, consuming alcohol, and more. In India, the mortality rate of OC is also higher [1]. There are commercial announcements about the difficulty of consuming alcohol and tobacco; but, because of insufficient knowledge and shortage of understanding, people should be quiet in the routine of tobacco and alcohol which leads to a rise in the counts of OC patients [2]. Major international organizations for research carried out a review and forecast the amount of cancer patients should rise from 1 million by 2012 to more than 1.7 million by 2035. It indicates that the mortality rate can also further improve from 680,000 to 2 million. Therefore, it will be of great significance for diagnosing OSCC at its earlier phase thereby the treatment will begin as early as potential, and the mortality rate because of OC will be decreased [3–4].

With the development of technology, several research workers for the earlier identification of OC have implemented continuous research work, and, simultaneously, a massive quantity of OC information is gathered and achieved accessible for exploration [5–7]. The most complex task for physicians is to properly forecast the variety and phase of cancer. The traditional technique employed by medical specialists is the physical screening in the initial phase and thereafter, for purpose of the conformity, a biopsy should be employed [8]. With the enhancement in computer technology, numerous machine learning (ML) methods besides image processing algorithms have been employed by research work for predicting the phase and variety of cancer, which will support medical specialists in providing the best treatment for OSCC patients [9]. Amongst various imaging methods, the histopathological imaging (HI) method is highly applicable for diagnosing OSCC. Consequently, we considered normal color images and HI of OSCC for identification and classification issues [10–12].

Computer-assisted diagnosis (CAD) increases patients' possibilities of survival over an earlier analysis of OSCC. Artificial intelligence (AI) technologies have contributed to different medical domains like analyzing medical images for earlier identification of diseases and cancers [13]. AI methods train models with a huge amount of the dataset thus, they achieve the capability and knowledge and store them, and later their effectiveness could be confirmed over novel images whose features have been removed and related to the kept features followed by categorized dependent upon the resemblance amongst the features of the novel image with the kept features (data trained) [14]. AI models functioned for recognizing biomarkers to predict OSCC, decrease the workload of doctors, and understand complex data in HI. In current times, deep learning (DL) models have been developed with higher capability for analyzing medical images equated with the effectiveness of human specialists.

This article presents an automated lion optimization algorithm with a deep transfer learning-based oral cancer detection and classification (LOADL-OCDC) approach. The LOADL-OCDC technique follows a multistage process. Initially, the LOADL-OCDC technique performs bilateral filtering-based noise elimination and CLAHE-based contrast improvement. Next, the EfficientNet model can be applied to learn complex and intrinsic feature patterns from the pre-processed images. In the presented LOADL-OCDC technique, the lion optimization algorithm (LOA) can be applied for fine-tuning the hyperparameters of the EfficientNet model. For cancer detection, the LOADL-OCDC technique applies a deep recurrent neural network (DRNN) model. The comprehensive comparison study reported the supremacy of the LOADL-OCDC approach in terms of dissimilar measures.

The present work is structured in a manner that, Section II provides a concise overview of recent research discoveries. In Section III, we present a comprehensive overview of our proposed methodology. The Discussion of results and the datasets utilized in our study are given under Section IV. Section V reports State of art comparison at last Section VI, concludes the paper.

2. RELATED WORKS

Ananthakrishnan et al. [15] intended to categorize carcinogenic and normal cells in the oral cavity by employing 2 various techniques to achieve higher accuracy. The primary method mines local binary patterns (LBP) and metrics obtained in a histogram of the database and was provided to numerous ML algorithms. Another technique employs an integration of random forest (RF) and NNs as a backbone feature extraction for classification. In [16], explore the most recent oral cancer classification methodologies employing digital image processing, with the results of reliability, performance, affordability, and outcomes being assessed. This study reviewed performances of various approaches and procedures proposed for classifying oral cancers. In [17], an innovative technique employing DL dependent upon a metaheuristic technique was developed to offer a precise cancer analysis tool. The authors initially utilize 3 preprocessing algorithms, comprising data augmentation, noise reduction, and Gamma correction for increasing the quality of the raw images as well as their numbers to offer sufficient data in the training of CNN.

Al Duhayyim et al. [18] presented a new CAD for OC employing Sailfish Optimizer with Fusion-based Classification (CADOC-SFOFC) technique. This system defines the presence of OC under medicinal pictures. To complete this, an integration-enabled feature extraction method was executed by implementing ResNet and VGGNet16 architecture. Further, feature vectors have been combined and entered into the extreme learning machine (ELM) algorithm for the categorization method. Additionally, the SFO method was applied in the efficient parameters choice of the ELM algorithm, therefore leading to superior performance. Warin et al. [19] developed to estimate the effectiveness of DCNN techniques for classifying and identifying OSCC and oral potentially malignant diseases (OPMDs) in oral HI. Nanditha et al. [20] introduced a study was an effort to design an automatic model to diagnose OC by utilizing DL methods. An ensemble DL technique that integrates the advantages of Resnet-50 and VGG-16 was established.

In [21], an innovative DL-based modified-CNN (MCNN) for correctly recognizing and categorizing the abnormal, and normal condition of oral cavity. The developed MCNN was an enhanced type of CNN wherein the parameters of CNN have been enhanced under the Stochastic gradient optimization (SGO) method for classifying either abnormal or normal. Begum and Vidyullatha [22] attempted to implement an automatic identification of malignant and benign oral sample HI by applying a DL-based CNN technique for the primary diagnoses of OSCC. Currently, four proposed pre-trained DL-CNN methods DenseNet201, InceptionNet, NASNetLarge, and Xception were chosen using the TL method.

3. THE PROPOSED METHOD

In this article, we have designed an automatic LOADL-OCDC methodology. The foremost intention of the LOADL-OCDC method is to recognize and classify the occurrence of oral cancer into distinct classes [23–24]. The LOADL-OCDC technique follows a multistage process namely image preprocessing, EfficientNet-based feature extraction, LOA-based hyperparameter, and DRNN-based classification processes. Figure 1 represents the entire flow of the LOADL-OCDC system.

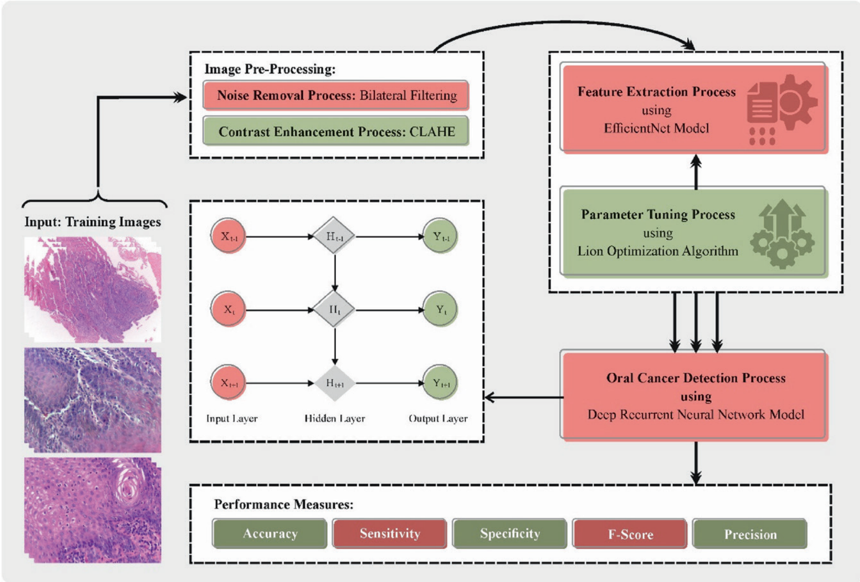

Figure 1. Overall flow of LOADL-OCDC approach

3.1 IMAGE PREPROCESSING

Initially, the LOADL-OCDC technique performs BF-based noise extraction and CLAHE-based contrast improvement. The proposed model starts its complete procedure by using BF for noise elimination, addressing a dangerous feature of oral cancer image study [25]. BF is chiefly effectual in maintaining significant edges and structures while instantaneously decreasing noise, certifying that the following phases of analysis are directed toward a cleaner and more advanced image. Following noise elimination, the model includes contrast-limited Adaptive Histogram Equalization (CLAHE) for improving the difference in oral cancer images. CLAHE adjusts its histogram equalization technique to local image areas, efficiently justifying issues connected to over-amplification of noise and safeguarding that related facts in changing areas of the oral cavity are correctly highlighted. By incorporating CLAHE and bilateral filtering, the LOADL-OCDC model struggles to enhance image quality, generating a basis for following phases of processing and analysis that donate to reliable and accurate oral cancer recognition. This multi-step model considers the method's promise to improve the visibility of vital features in oral images, finally helping in the initial and exact identification of possible oral cancer anomalies.

3.2 EFFICIENTNET MODEL

The EfficientNet model can be applied to learn complex and intrinsic feature patterns from the pre-processed images. EfficientNet projected by Le and Tan is recognized for its efficacy and accuracy and has 8 variations (B0-B7) [26]. Model range in CNN is a challenging task owing to the tradeoff between accuracy and efficacy. Improving the depth of the method can enhance precision whereas enlarging the resolution and width of input images can also main to a superior solution. EfficientNet has 3 significant parameters such as depth, resolution, and width utilizing compound scaling. The depth and breadth have been enlarged by 10 and 20 percent, correspondingly, whereas the image resolution has been improved by 15 percent to attain the finest result. Scaling multipliers such as Beta, Gamma, and Alpha are employed to compute the width, resolution, and depth utilizing Eqs. (1), (2), and (3), by an extra user-specific co-efficient named Phi. Figure 2 determines the infrastructure of the EfficientNet model.

In this research, EfficientNet-B0 is only employed as the base method. MB Conv is the main structure block of EfficientNet which contains an excitation and squeeze optimizer block. The block of MB Conv is parallel to the

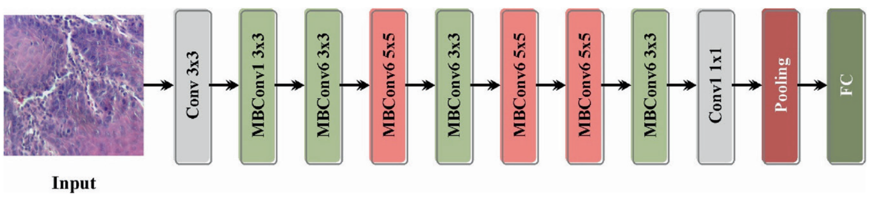

Figure 2. Framework of EfficientNet

reversed blocks in MobileNetV2 and contains a 3×3 depth and point-wise convolution to decrease output networks.

$$Depth{:}\ d = \alpha\varphi \tag{1}$$

$$Width{:}\ w = \beta\varphi \tag{2}$$

$$Resolution{:}\ r = \gamma\varphi \tag{3}$$

Where: $\alpha \times \beta \times 2 \times r \times 2 \approx 2; \alpha \geq 1, \beta \geq$ and $\gamma \geq 1$

3.3 LOA BASED HYPERPARAMETER TUNING

In this work, the LOA can be applied to fine-tuning the hyperparameters of the EfficientNet system. LOA assists as a metaheuristic technique where a set of produced results at random recognized as lions is established. N solutions create the population whereas every solution covers features α and β that need to be enhanced. The solution is signified as follows:

$$Solution\ (Lion) = [\alpha, \beta]$$

In the original population (N), some lions form migrants and the leftover population was chosen as Prides (P) randomly. Amid migrant lions, S% of the persons are female and leftovers are male. The solutions cover dissimilar mixtures of brightness and dissimilarity.

Some lions of female from every pride hunt for targets in clusters to help their pride. The searchers regularly hold their individual exact empirical for catching and encircling the target. Generally, the lioness tracks a similar design for chasing their victim. Throughout the hunting process, every lioness alters its place utilizing its present place and also the locations of its cluster members. Generally, hunters violent their target from opposite directions for the exact aim, and therefore the opposition-based learning method is employed here which is superior for resolving optimizer issues. Lions are separated into three groups such as left, center, and right.

The classification accuracy of the RF system signifies the value of the fitness of every lion. The best-attained solution in the prior iteration is denoted as the finest visited place for every lion and it is upgraded as an optimizer procedure development. Territorial Takeover is the method of recollecting the finest female and male solutions that are proficient in outdoing novel solutions to an assumed amount. Hunter used to enhance his fitness always and simultaneously, PREY generally tries to escape from the chaser, and its new location is assessed in Eq. (4).

$$PRE\ Y' = PREY + r\ and(0,1)\ x\ PI\ x\ (PREY — Hunter) \tag{4}$$

Whereas Hunter denotes the novel location utilized to violent the prey, PREY signifies the present position, and PI refers to the percentage of the hunter's fitness development.

The prey encircling for right and left groups are provided by Eq. (5) as

$$Hunter' = \begin{cases} rand\left((2\times PREY - Hunter), PREY\right) \\ (2\times PREY - Hunter) < PREY \\ rand\left(PREY, (2\times PREY - Hunter)\right) \\ (2\times PREY - Hunter) > PREY \end{cases} \tag{5}$$

Whereas Hunter denotes the present position and Hunter' specifies the new place. The upgraded places of center hunters have been signified by utilizing Eq. (6).

$$Hunter' = \begin{cases} rand(PREY, Hunter), Hunter > PREY \\ rand(Hunter, PREY), hunter < PREY \end{cases} \tag{6}$$

The areas of every pride cover the individual finest solution of all of its followers which aid to hold the greatest solution for the system. Over the iteration, they are employed to enhance the results of the Lion Optimizer method. The novel locations for female lions are denoted by Eq. (7).

$$\begin{aligned} Lion' = {} & Female\ Lion + 2 \times D \times rand\ (0,1)\{R1\} \\ & + U(-1,1) \times tan() \times D \times \{R2\} \end{aligned} \tag{7}$$

$$\{R1\} \cdot \{R2\} = 0$$

$$\|\{R2\}\| = 1$$

From the above-mentioned equation, Female Lion indicates the lion's present location, and D specifies the lion's location recognized utilizing event collection in the pride's area. The $\{R1\}$ specifies the early position which is an earlier place of the lion and its head near $\{R2\}$. The vectors $\{R1\}$ and $\{R2\}$ are vertical to each other. Also, the local male lion travels to a few nominated places at random and if the recognized novel locations are superior to the prior one, it directly upgrades its local finest solution.

After this, mating is complete to generate novel offspring. Predefined c% of female lions in each pride acquires navigated over with many random local males. However, migrant lions only mate with one random male. The dual offspring have been produced utilizing the Eqs. (8) and (9).

$$\begin{aligned} offspring_j 1 = {} & \beta \times FemaleLion_j \\ & + \sum \frac{1-\beta}{\sum_{i=1}^{NR} S_i} \times MaleLion_j^i \times S_i \end{aligned} \tag{8}$$

$$offspring_j 2 = (1-\beta)\times FemaleLion_j + \sum \frac{\beta}{\sum_{i=1}^{NR} S_i}\times MaleLion_j^i \times S_i \quad (9)$$

Whereas j denotes the dimension, if male i is employed for crossover then S_i will have a value of 1 or else 0, NR directs the number of local males present in the pride and β signifies a random value which has standard deviation and mean value as 0.1 and 0.5, respectively. Dual random offspring produced are nominated as female and male. M% of genetic material is transformed where few random numbers substitute them. The lions with the lowest fitness are extracted out of the pride and become migrants while the highest fitness lions are reserved and become local males.

Throughout the migration process, some arbitrarily nominated female lions become migrants. The new and old migrants are organized by employing their fitness values. The system is finished when an identified CPU time, amount of iterations, or essential value of fitness is attained. Lastly, the solution with the finest fitness was selected and the equivalent values of α and β are preferred for additional optimizer of contrast and brightness.

In the binarization process, the values of pixels are divided into white and black types (0 and 1). It is essential to differentiate the objects of attention from the background in image improvement or study issues. BGR color image is transformed into a grayscale image and then converted to an image binary. Otsu's method implements binarization.

Otsu's method generally tracks adaptive threshold to binarize the pictures. The finest value of the threshold is assessed by evaluating the class variance of all probable values of the threshold from to 255. At first, an input image is generated and to enhance the threshold, the least class variance is found.

$$\sigma^2 = \frac{\sum_{i=1}^{N}(X_i-\mu)^2}{N} \quad (10)$$

Where σ^2 denotes the variance; X_i signifies the value of pixel, N and μ represents the amount and mean of pixels in the image.

The LOA model originates a fitness function (FF) to recognize higher classifier performance. It defines an optimistic number to signify the greater candidate solution performance. In this research, the error rate of classifier minimization is measured as FF and assumed in Eq. (24).

$$fitness(x_i) = Classifier\ ErrorRate\ (x_i) = \frac{No.\ of\ misclassified\ sample}{Total\ No.\ of\ sample} * 100 \quad (11)$$

3.4 CANCER DETECTION USING THE DRNN MODEL

Eventually, the LOADL-OCDC technique applies the DRNN model for cancer detection and classification model. RNN is a deep neural network model with a loop inside [27]. The recursive connectivity can hold the data from the historical input. Thus, RNNs could model data sequences effectively with temporal dependency. The data sequence $x \in R^{p\times T}$ is fed as input to the RNN. Data at time step T has a p component. The output is y. $s_t \in R^n$ refers to the intermediate HL at t time step that is reliant on the existing input x_t and s_{t-1} refers to the HL of the prior time step. n denotes the number of hidden units. The HL is considered as network memory which holds the data captured by the prior steps. The HL at t time step is computed by Eq. (12).

$$s_t = f(Vx_t + Ws_{t-1} + b_s) \quad (12)$$

Now, the activation function is f. The novel input which forms the input to HL is represented as $v \in R^{n\times p}$. The weight matrix between HLs that control the memory is denoted as $W \in R^{n\times n}$. $b_s \in R^{n\times 1}$ a bias vector. Thus, the present HL relies on the existing input and the prior HL having the memory of prior data.

The RNN training is the same as the training of classical FCN using the BP model. Different from the classical NN, the RNN shares a similar parameter through each time step. Thus, the gradient relies on the existing and the prior time steps. This BP model is known as backpropagation through time (BPTT). But the simple RNN has gradient disappearing problems. The gradient error about prior input can quickly disappear once the model is trained through BPTT. Thus, the RNN can perfect long-term dependence owing to this issue.

4. RESULT ANALYSIS AND DISCUSSION

The LOADL-OCDC technique is simulated using the Python 3.8.5 tool. The performance evaluation of the LOADL-OCDC model is verified utilizing the NDB-UFES dataset [28], comprising 237 instances with three classes as demonstrated in Table 1. Figure 3 illustrates the sample images.

Figure 4 establishes the classifier results of the LOADL-OCDC system below the test dataset. Figures. 4a-4b portrays the confusion matrix presented by the LOADL-OCDC technique at 70:30 of TRAP/TESP. The figure indicated that the LOADL-OCDC approach has detected and classified all 3 classes exactly. Similarly, Figure 4c defines the PR analysis of the LOADL-OCDC model. The figure described that the LOADL-OCDC technique has achieved the highest PR performance under all

Table 1. Details of the dataset

Class Name	Class Label	No. of Samples
Oral Squamous Cell Carcinoma	Class-0	91
Oral Leukoplakia with Dysplasia	Class-1	89
Oral Leukoplakia without Dysplasia	Class-2	57
Total No. of Samples		**237**

classes. Finally, Figure 4d determines the ROC study of the LOADL-OCDC technique. The figure shows that the LOADL-OCDC method has resulted in proficient outcomes with the greatest ROC values below separate classes.

In Table 2 and Figure 5, the detection outcomes of the LOADL-OCDC system are provided under 70% of TRAP and 30% of TESP. The results imply that the LOADL-OCDC approach properly categorized three classes. With 70% of TRAP, the LOADL-OCDC model classifies the class-0 samples with $accu_y$ of 91.52%, $prec_n$ of 89.09%, $sens_y$ of 85.96%, $spec_y$ of 94.44%, and F_{score} of 87.50%. Also, with 70% of TRAP, the LOADL-OCDC method categorizes the class-1 samples with an $accu_y$ of 90.91%, $prec_n$ of 84.93%, $sens_y$ of 93.94%, $spec_y$ of 88.89%, and F_{score} of 89.21%. Additionally, with 70% of TRAP, the LOADL-OCDC approach classifies the class-2 samples with an $accu_y$ of 93.33%, $prec_n$ of 91.89%, $sens_y$ of 80.95%, $spec_y$ of 97.56%, and F_{score} of 86.08%. Meanwhile, with 30% of TESP, the LOADL-OCDC system classifies the class-0 samples with $accu_y$ of 91.67%, $prec_n$ of 93.75%, $sens_y$ of 88.24%, $spec_y$ of 94.74%, and F_{score} of 90.91%. Furthermore, with 30% of TESP, the LOADL-OCDC procedure classifies the class-1 samples with $accu_y$ of 93.06%, $prec_n$ of 84.62%, $sens_y$ of 95.65%, $spec_y$ of 91.84%, and F_{score} of 89.80%.

The $accu_y$ curves for training (TRA) and validation (VL) offered in Figure 7 for the LOADL-OCDC approach deliver respected visions into its performance under many epochs. Mainly, there is endless development in both TRA and TES $accu_y$ with increasing epochs, signifying the model's capability to recognize and learn designs from both TRA and TES data. The rising trend in TES $accu_y$ underlines the model's flexibility to the TRA dataset and its ability to make precise predictions on hidden data, highlighting strong generalized aptitudes.

Figure 8 provides a widespread summary of the TRA and TES loss values for the LOADL-OCDC method across many epochs. The TRA loss gradually reduces as the method improves its weights to minimize errors of classification on both datasets. The loss curves determine the model's position with the TRA data, underlining its ability to take designs effectually in both datasets.

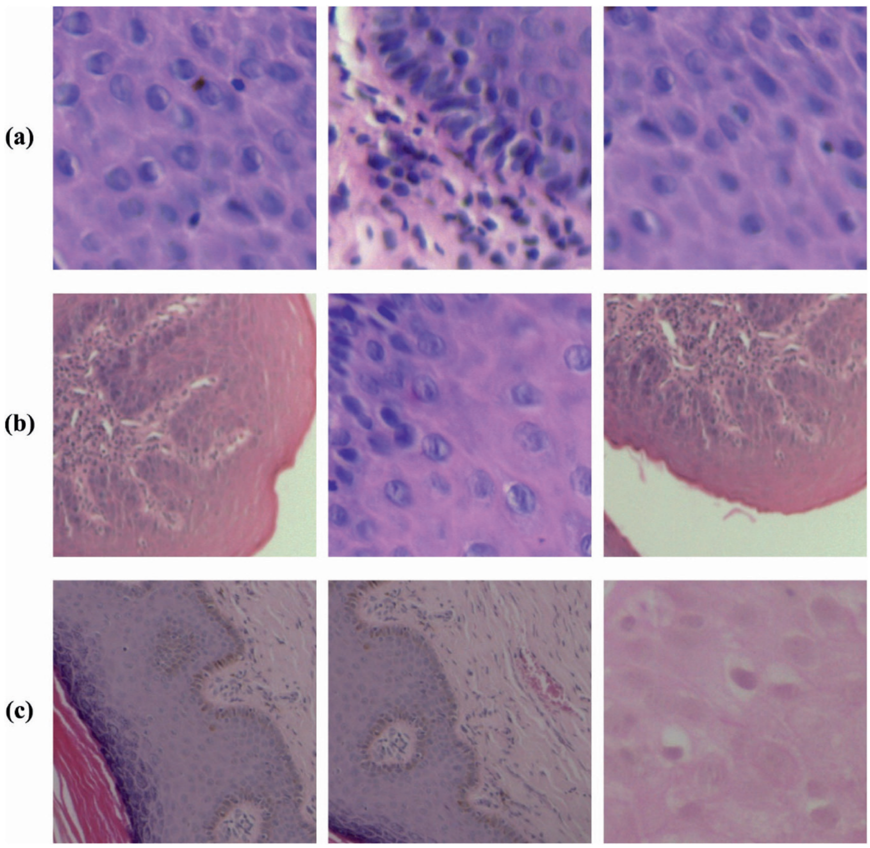

Figure 3. Sample images a) Class-0 b) Class-1 c) Class-2

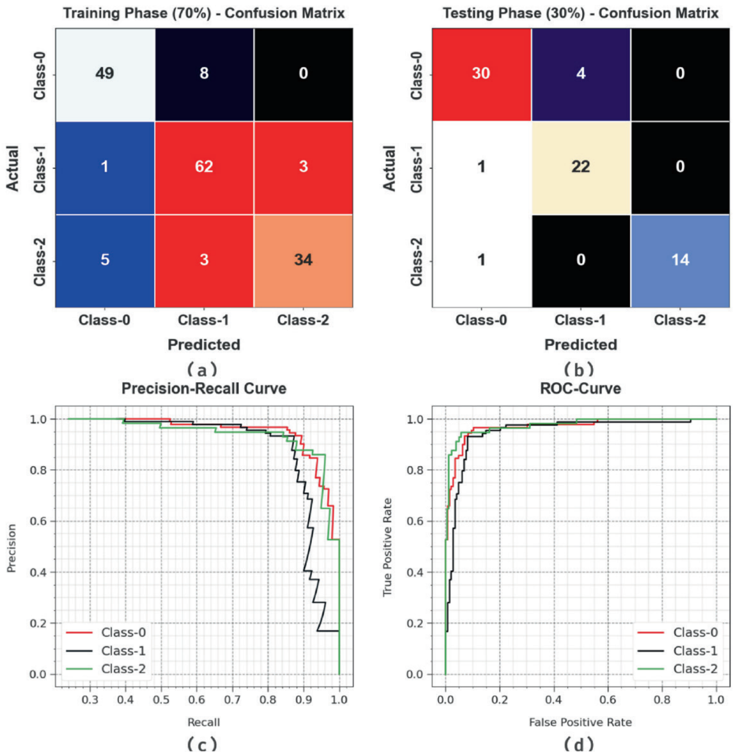

Figure 4. Classifier analysis of (a-b) Confusion matrices and (c-d) PR and ROC curves

Table 2. Detection result of LOADL-OCDC technique on 70:30 of TRAP/TESP

Class Labels	$Accu_y$	$Prec_n$	$Sens_y$	$Spec_y$	F_{Score}
TRAP (70%)					
Class-0	91.52	89.09	85.96	94.44	87.50
Class-1	90.91	84.93	93.94	88.89	89.21
Class-2 93.33		91.89	80.95	97.56	86.08
Average	**91.92**	**88.64**	**86.95**	**93.63**	**87.59**
TESP (30%)					
Class-0	91.67	93.75	88.24	94.74	90.91
Class-1	93.06	84.62	95.65	91.84	89.80
Class-2	98.61	100.00	93.33	100.00	96.55
Average	**94.44**	**92.79**	**92.81**	**95.52**	**92.42**

Noteworthy is the constant modification of parameters in the LOADL-OCDC system, intended to reduce differences between predictions and actual TRA labels.

Table 3 shows the Comparative study of OCDC method based on DRNN with and without optimization algorithm. The Experimental results for DRNN based OCDC is $accu_y$ of 92.52%, $prec_n$ of 90.50%, $sens_y$ of 87.82%, $spec_y$ of 93.74% and f_{score} of 90.67%. In the presented LOADL-OCDC technique, the lion optimization algorithm (LOA) can be applied for fine-tuning the hyperparameters of the EfficientNet model. For cancer detection, the LOADL-OCDC technique applies a deep recurrent neural network (DRNN) system to obtain better results.

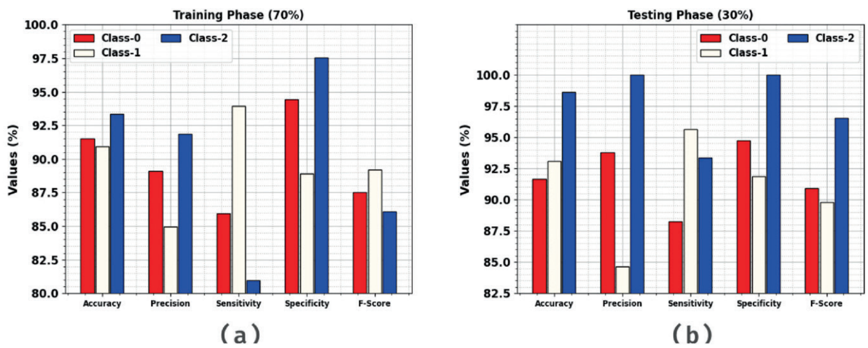

Figure 5. Detection result of LOADL-OCDC technique (a) 70% of TRAP and (b) 30% of TESP An average detection result of the LOADL-OCDC technique is depicted in Figure 6. The experimental values emphasized that the LOADL-OCDC approach properly categorized three classes. With 70% of TRAP, the LOADL-OCDC method obtains an average $accu_y$ of 91.92%, $prec_n$ of 88.64%, $sens_y$ of 86.95%, $spec_y$ of 93.63%, and F_{score} of 87.59%. Moreover, with 30% of TESP, the LOADL-OCDC system gets an average $accu_y$ of 94.44%, $prec_n$ of 92.79%, $sens_y$ of 92.81%, $spec_y$ of 95.52%, and F_{score} of 92.42%.

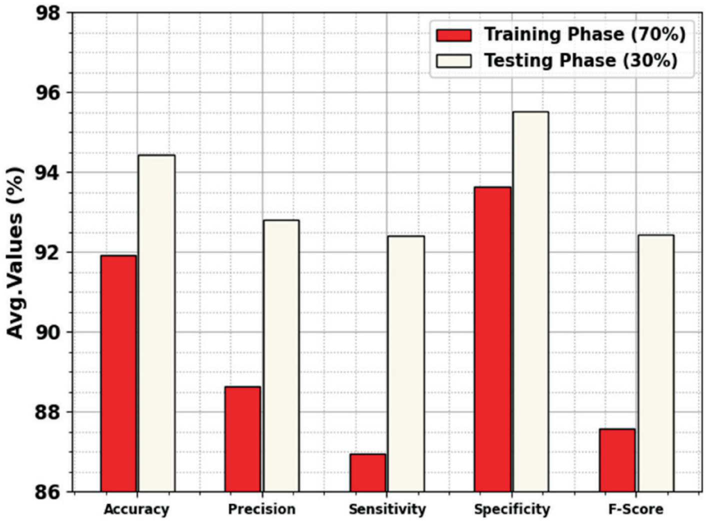

Figure 6. Average of LOADL-OCDC technique on 70:30 of TRAP/TESP

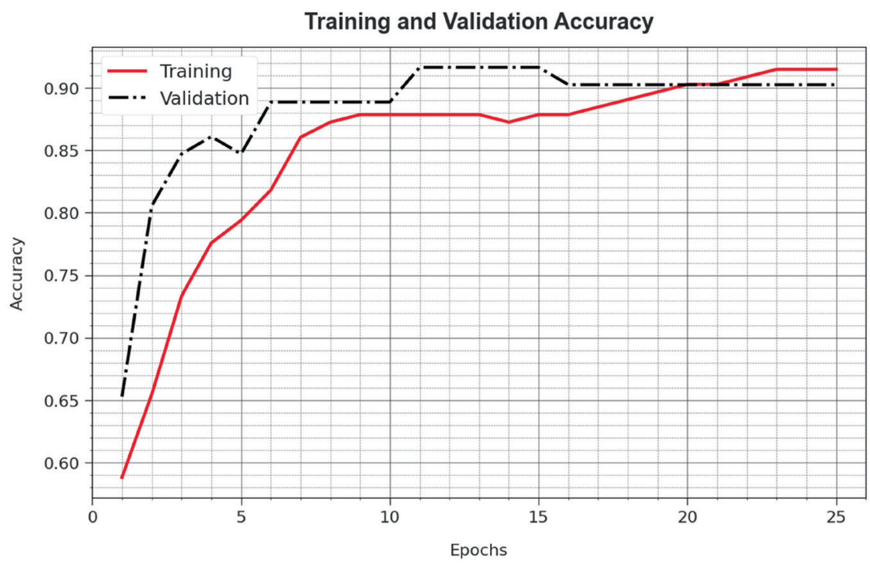

Figure 7. $Accu_y$ curve of the LOADL-OCDC technique

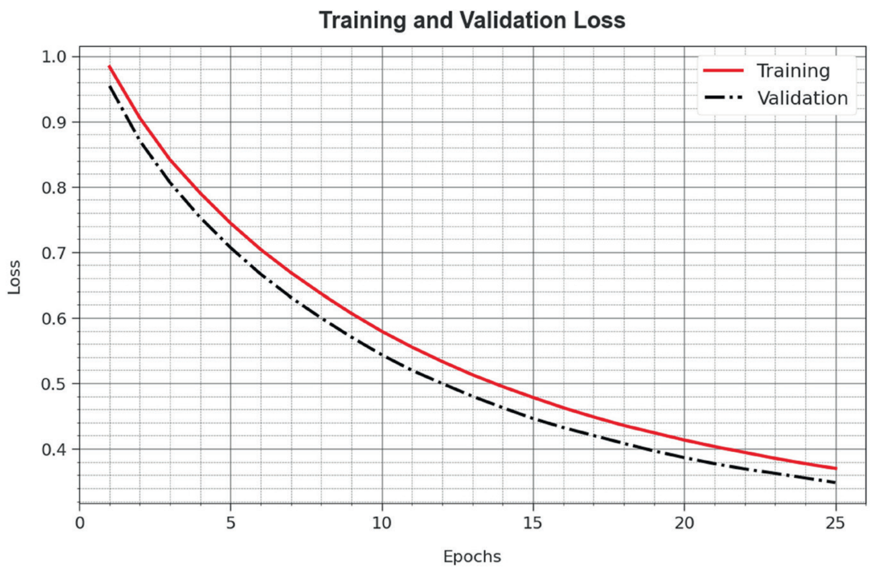

Figure 8. Loss curve of the LOADL-OCDC technique

Table 3. Comparative analysis of the LOADL-OCDC system with existing models

Model	Methods	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F-score (%)
Existing model	DRNN based OCDC	92.52	90.50	87.82	93.74	90.67
Proposed model	LOADL_DRNN based OCDC	**94.44**	**92.79**	**92.81**	**95.52**	**92.42**

Table 4. Proposed method compared with Earlier researches.

Reference	Methods	Accuracy	Precision	Sensitivity	Specificity	F1-score
Proposed method	LOADL_OCDC	**94.44**	**92.79**	**92.81**	**95.52**	**92.42**
Mira et al (2024) [29]	HRNet-W18	84.3%	85.47%	83%	96%	83.6%
Das et al (2023) [30]	ALEXNET	88%	88%	89%	88%	89%
Atta-ur, et al. (2022) [31]	AlexNet_CNN	90.02	87.69	92.74	87.38	90.15
Tanriver et al (2021) [32]	DenseNet-161	85.21%%	87.9%	84.1%	91.23%	84.4%
Welikala et al (2020) [33]	ResNet-101	81.37	84.77	89.51	62.29	87.07
Panigrahi et al (2019) [34]	Faster RCNN	92.1%	–	90.2%	–	75.9%
Alhazmi, Anwar, et al. (2021) [35]	ANN	78.95	85.71	85.71	60.01	–

Table 5. Comparative analysis of the LOADL-OCDC system with other existing models

Methods	Accuracy	Precision	Sensitivity	Specificity	F-score
VGG16	74.68	74.55	74.73	78.67	81.34
VGG19	71.79	70.73	71.61	74.52	80.11
ALEXNET	88.66	88.59	89.60	88.65	86.76
RESNET 50	91.60	91.57	92.19	92.56	90.17
RESNET 101	89.52	89.51	90.77	88.57	82.64
INCEPTION NET	92.78	92.09	91.64	92.53	89.90
MOBILENET	93.50	91.64	91.71	92.79	90.02
LOADL-OCDC	94.44	92.79	92.81	95.52	92.42

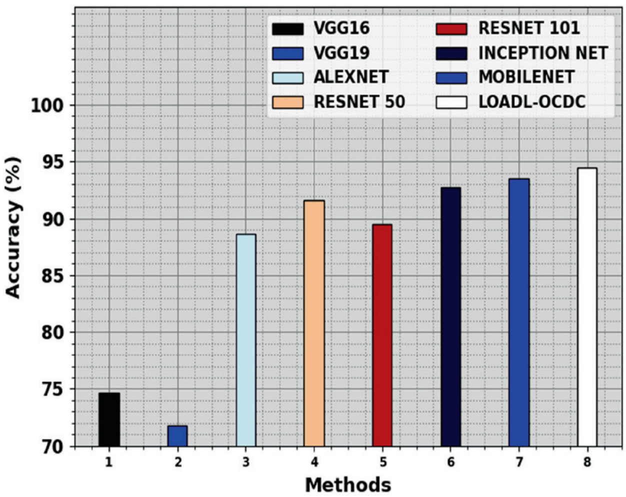

Figure 9. $Accu_y$ analysis of LOADL-OCDC technique with existing methods

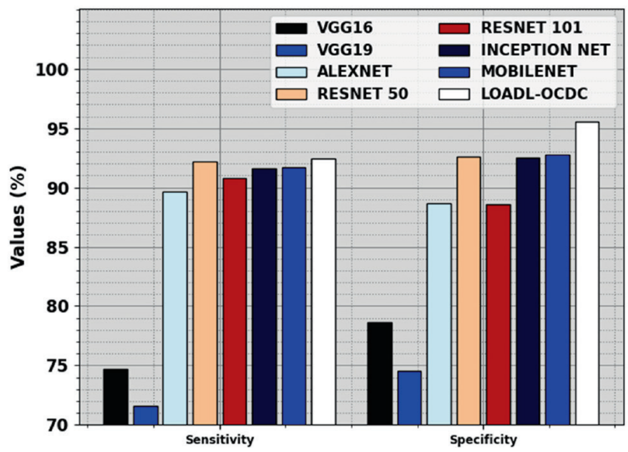

Figure 10. $Sens_y$ and $spec_y$ analysis of LOADL-OCDC technique with existing methods

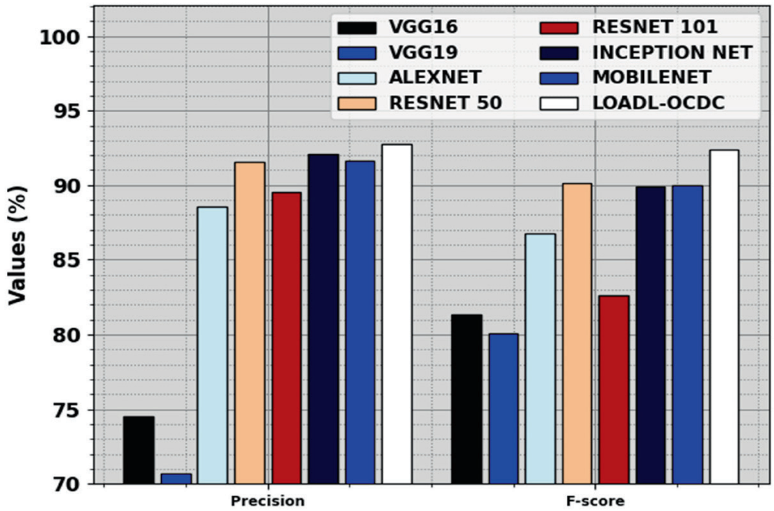

Figure 11. $prec_n$ and F_{score} analysis of LOADL-OCDC technique with existing methods

5. STATE OF ART COMPARISON WITH EARLIER APPROACHES

In general, the Table 4 offers a thorough summary of how different models compare in terms of their performance, based on the indicators that were analysed.

Table 5 signifies a comparison study of the LOADL-OCDC model in terms of distinct measures. In Figure 9, a comparative analysis of the LOADL-OCDC technique is provided in terms of $accu_y$ and $prec_n$. The experimental values inferred that the LOADL-OCDC technique reaches improved values of $accu_y$ and $prec_n$. Based on $accu_y$, the LOADL-OCDC technique gains a higher $accu_y$ of 94.44% while the VGG16, VGG9, AlexNet, ResNet50, ResNet101, InceptionNet, and MobileNet models obtain lower $accu_y$ of 74.68%, 71.79%, 88.66%, 91.60%, 89.52%, 92.78%, and 93.50%.

In Figure 10, a comparative study of the LOADL-OCDC system is delivered in terms of $sens_y$ and $spec_y$. The experimental values concluded that the LOADL-OCDC method attains enhanced values of $sens_y$ and $spec_y$. Based on $sens_y$, the LOADL-OCDC model increases the greatest $sens_y$ of 92.81% while the VGG16, VGG9, AlexNet, ResNet50, ResNet101, InceptionNet, and MobileNet methodologies gain lower $sens_y$ of 74.73%, 71.61%, 89.60%, 92.19%, 90.77%, 91.64%, and 91.71%, respectively. Meanwhile, based on $spec_y$, the LOADL-OCDC system attains higher $spec_y$ of 95.52% but the VGG16, VGG9, AlexNet, ResNet50, ResNet101, InceptionNet, and MobileNet approaches get lower $spec_y$ of 78.67%, 74.52%, 88.65%, 92.56%, 88.57%, 92.53%, and 92.79%, correspondingly. These results confirmed the better performance of the LOADL-OCDC approach over other present models.

In Figure 11, a comparative study of the LOADL-OCDC system is delivered in terms of $prec_n$ and F_{score}. Meanwhile, based on $prec_n$, the LOADL-OCDC system increases the highest $prec_n$ of 92.79% whereas the VGG16, VGG19, AlexNet, ResNet50, ResNet101, InceptionNet, and MobileNet approaches get lower $prec_n$ of 74.55%, 70.73%, 88.59%, 91.57%, 89.51%, 92.09%, and 91.64%, respectively. The experimental values concluded that the LOADL-OCDC method attains enhanced values of $f_{score.}$

6. CONCLUSION

In this article, we have introduced an automated LOADL-OCDC methodology. The foremost intention of the LOADL-OCDC method is to recognize and classify the occurrence of oral cancer into distinct classes. The LOADL-OCDC technique follows a multistage process. Initially, the LOADL-OCDC technique performs bilateral filtering-based noise extraction and CLAHE-based contrast enhancement. Next, the EfficientNet model can be applied to learn complex and intrinsic feature patterns from the pre-processed images. In the presented LOADL-OCDC technique, the LOA can be applied for fine-tuning the hyperparameters of the EfficientNet model. For cancer detection, the LOADL-OCDC technique applies the DRNN model. An extensive experimental study is created to investigate the detection results of the LOADL-OCDC technique. The complete contrast study reported the supremacy of the LOADL-OCDC system in terms of dissimilar measures.

6. REFERENCES

1. LIN, H., CHEN, H., WENG, L., SHAO, J. and LIN, J., 2021. Automatic detection of oral cancer in smartphone-based images using deep learning for early diagnosis. *Journal of Biomedical Optics*, *26*(8), pp.086007–086007.
2. CHANG, X., YU, M., LIU, R., JING, R., DING, J., XIA, J., ZHU, Z., LI, X., YAO, Q.,

ZHU, L. and ZHANG, T., (2023). Deep learning methods for oral cancer detection using Raman spectroscopy. *Vibrational Spectroscopy*, *126*, p.103522.

3. WARIN, K., LIMPRASERT, W., SUEBNUKARN, S., JINAPORNTHAM, S. and JANTANA, P., (2021). Automatic classification and detection of oral cancer in photographic images using deep learning algorithms. *Journal of Oral Pathology & Medicine*, *50*(9), pp.911–918.
4. SHAMIM, M.Z.M., SYED, S., SHIBLEE, M., USMAN, M., ALI, S.J., HUSSEIN, H.S. and FARRAG, M., (2022). Automated detection of oral pre-cancerous tongue lesions using deep learning for early diagnosis of oral cavity cancer. *The Computer Journal*, *65*(1), pp.91–104.
5. SRINIVASA SAI ABHIJIT CHALLAPALLI. (2024). Sentiment Analysis of the Twitter Dataset for the Prediction of Sentiments. *Journal of Sensors, IoT & Health Sciences*, *2*(4), 1–15.
6. FU, Q., CHEN, Y., LI, Z., JING, Q., HU, C., LIU, H., BAO, J., HONG, Y., SHI, T., LI, K. and ZOU, H., (2020). A deep learning algorithm for detection of oral cavity squamous cell carcinoma from photographic images: A retrospective study. *EClinicalMedicine*, *27*.
7. SRINIVASA SAI ABHIJIT CHALLAPALLI. (2024). Optimizing Dallas-Fort Worth Bus Transportation System Using Any Logic. *Journal of Sensors, IoT & Health Sciences*, *2*(4), 40–55.
8. AL-RAWI, N., SULTAN, A., RAJAI, B., SHUAEEB, H., ALNAJJAR, M., ALKETBI, M., MOHAMMAD, Y., SHETTY, S.R. and MASHRAH, M.A., (2022). The effectiveness of artificial intelligence in the detection of oral cancer. *international dental journal*, *72*(4), pp.436–447.
9. K. VINAY KUMAR, SUMANASWINI PALAKURTHY, SRI HARSHA BALIJADA-DDANALA, SHARMILA REDDY PAPPULA, and ANIL KUMAR LAVUDYA. (2024). Early Detection and Diagnosis of Oral Cancer Using Deep Neural Network. *Journal of Computer Allied Intelligence*, *2*(2), 22–34.
10. SWAPNA SATURI, GUNDETI NAVEEN KUMAR, NAMILLA SIRI, KOTA MADHURI, and VALLAPUREDDY YASHWANTH REDDY. (2025). Deep Learning for Understanding Multi label Imbalanced Chest X-rayDatasets. *Journal of Computer Allied Intelligence(JCAI, ISSN: 2584–2676)*, *3*(1), 40-47.
11. FIGUEROA, K.C., SONG, B., SUNNY, S., LI, S., GURUSHANTH, K., MENDONCA, P., MUKHIA, N., PATRICK, S., GURUDATH, S., RAGHAVAN, S. and IMCHEN, T., (2022). Interpretable deep learning approach for oral cancer classification using guided attention inference network. *Journal of biomedical optics*, *27*(1), pp.015001–015001.
12. YANG, Z., PAN, H., SHANG, J., ZHANG, J. AND LIANG, Y., (2023). Deep-Learning-Based Automated Identification and Visualization of Oral Cancer in Optical Coherence Tomography Images. *Biomedicines*, *11*(3), p.802.
13. ALABI, R.O., ALMANGUSH, A., ELMUSRATI, M. and MÄKITIE, A.A., (2022). Deep machine learning for oral cancer: from precise diagnosis to precision medicine. *Frontiers in Oral Health*, *2*, p.794248.
14. AMIN, I., ZAMIR, H. and KHAN, F.F., (2021). Histopathological image analysis for oral squamous cell carcinoma classification using concatenated deep learning models. *medRxiv*, pp.2021–05.
15. ANANTHAKRISHNAN, B., SHAIK, A., KUMAR, S., NARENDRAN, S.O., MATTU, K. and KAVITHA, M.S., (2023). Automated Detection and Classification of Oral Squamous Cell Carcinoma Using Deep Neural Networks. *Diagnostics*, *13*(5), p.918.
16. HUANG, Q., DING, H. and RAZMJOOY, N., (2023). Optimal deep learning neural network using ISSA for diagnosing oral cancer. *Biomedical Signal Processing and Control*, *84*, p.104749.
17. AL DUHAYYIM, M., MALIBARI, A., DHAHBI, S., NOUR, M.K., AL-TURAIKI, I., OBAYYA, M.I. and MOHAMED, A., (2023). Sailfish Optimization with Deep Learning Based Oral Cancer Classification Model. *Comput. Syst. Sci. Eng.*, *45*(1), pp.753–767.
18. WARIN, K., LIMPRASERT, W., SUEBNUKARN, S., JINAPORNTHAM, S., JANTANA, P. and VICHARUEANG, S., (2022). AI-based analysis of oral lesions using novel deep convolutional neural networks for early detection of oral cancer. *Plos one*, *17*(8), p.e0273508.
19. NANDITHA, B.R., GEETHA, A., CHANDRASHEKAR, H.S., DINESH, M.S. and MURALI, S., (2021). An ensemble deep neural network approach for oral cancer screening.
20. PRABHAKARAN, R. and MOHANA, J., (2023). Stochastic gradient descent-based convolutional neural network to detect and classify oral cavity cancer. *Soft Computing*, *27*(13), pp.9169–9178.
21. BEGUM, S.H. and VIDYULLATHA, P., (2023). Deep Learning Model for Automatic Detection of Oral squamous cell carcinoma (OSCC) using Histopathological Images. *International Journal of Computing and Digital Systems*.
22. RAVIKUMAR, M., RACHANA, P.G., SHIVAPRASAD, B.J. and GURU, D.S., (2021). Enhancement of mammogram images using CLAHE and bilateral filter approaches.

In *Cybernetics, Cognition and Machine Learning Applications: Proceedings of ICCCMLA 2020* (pp. 261–271). Springer Singapore.

23. ARGHO, A.G., MASWOOD, M.M.S., MAHMOOD, M.I. and MONDOL, N., (2023). EfficientCovNet: A CNN-based approach to detect various pulmonary diseases including COVID-19 using modified EfficientNet. *Intelligent Systems with Applications*, p.200315.
24. PRIYA, R.D., KARTHIKEYAN, S., INDRA, J., KIRUBASHANKAR, S., ABRAHAM, A., GABRALLA, L.A., SIVARAJ, R. and NANDHAGOPAL, S.M., (2023). Self-Adaptive Hybridized Lion Optimization Algorithm with Transfer Learning for Ancient Tamil Character Recognition in Stone Inscriptions. *IEEE Access*.
25. XIA, M., ZHENG, X., IMRAN, M. and SHOAIB, M., (2020). Data-driven prognosis method using hybrid deep recurrent neural network. *Applied Soft Computing*, *93*, p.106351.
26. RIBEIRO-DE-ASSIS, M.C.F., SOARES, J.P., DE LIMA, L.M., DE BARROS, L.A.P., GRÃO-VELLOSO, T.R., KROHLING, R.A. and CAMISASCA, D.R., (2023). NDB-UFES: An oral cancer and leukoplakia dataset composed of histopathological images and patient data. *Data in Brief*, *48*, p.109128.
27. DAS, M., DASH, R. and MISHRA, S.K., (2023). Automatic detection of oral squamous cell carcinoma from histopathological images of oral mucosa using deep convolutional neural network. *International Journal of Environmental Research and Public Health*, *20*(3), p.2131.
28. SATHISHKUMAR, R., and GOVINDARAJAN, M. (2023). A Comprehensive Study on Artificial Intelligence Techniques for Oral Cancer Diagnosis: Challenges and Opportunities. In 2023 International Conference on System, Computation, Automation and Networking (ICSCAN) (pp. 1–5). IEEE.
29. MIRA, E. S., SAPRI, A. M. S., ALJEHANI, R. F., JAMBI, B. S., BASHIR, T., EL-KENAWY, E. S. M., and SABER, M. (2024). Early Diagnosis of Oral Cancer Using Image Processing and Artificial Intelligence. Fusion: Practice and Applications, 14(1), 293–308.
30. DAS, M., DASH, R., and MISHRA, S. K. (2023). Automatic detection of oral squamous cell carcinoma from histopathological images of oral mucosa using deep convolutional neural network. International Journal of Environmental Research and Public Health, 20(3), 2131.
31. RAHMAN, A. U., ALQAHTANI, A., ALDHAFFERI, N., NASIR, M. U., KHAN, M. F., KHAN, M. A., and MOSAVI, A. (2022). Histopathologic oral cancer prediction using oral squamous cell carcinoma biopsy empowered with transfer learning. Sensors, 22(10), 3833.
32. TANRIVER, G., SOLUK TEKKESIN, M., and ERGEN, O. (2021). Automated detection and classification of oral lesions using deep learning to detect oral potentially malignant disorders. Cancers, 13(11), 2766.
33. WELIKALA, R. A., REMAGNINO, P., LIM, J. H., CHAN, C. S., RAJENDRAN, S., KALLARAKKAL, T. G., ... and BARMAN, S. A. (2020). Automated detection and classification of oral lesions using deep learning for early detection of oral cancer. IEEE Access, 8, 132677–132693.
34. PANIGRAHI, S. SWARNKAR, T. AUTOMATED Classification of Oral Cancer Histopathology images using Convolutional Neural Network. In 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM); IEEE: New York, NY, USA, 2019; pp. 1232–1234.
35. ALHAZMI, A., ALHAZMI, Y., MAKRAMI, A., MASMALI, A., SALAWI, N., MASMALI, K., and PATIL, S. (2021). Application of artificial intelligence and machine learning for prediction of oral cancer risk. Journal of Oral Pathology & Medicine, 50(5), 444–450.