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# Optimal Deep Learning Convolutional Neural Network-Based Oral Cancer Detection Model

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**Abstract**
Oral cancers continue to pose a serious challenge to global health, particularly in developing regions such as India. Lack of automated systems for early visual screening leads to late diagnoses of many patients and subsequently results in high morbidity rates due to the high rate of late-stage diagnosis. For these reasons, finding more efficient means of early identification of oral cancers is essential; however, current methods of diagnosis either take a long time, are subjective (i.e., determined by a single individual), or require an expert in oral pathology to assess patient examination results. Therefore, this study's primary objective is to propose an advanced deep learning model for the detection of oral cancer using a combined deep convolutional neural network–long short-term memory architecture. The education will utilize the publicly available oral cancer dataset, which consists of various labelled images of oral squamous cell carcinoma. First, various preprocessing approaches, including cropping images and applying Contrast Limited Adaptive Histogram Equalisation to recover image excellence, will be applied to the images before extracting features from each image using a DCNN. Next, the most recent Hybrid Horse Herd Lion Optimisation (HHHLO) approach will be used to select the optimal features for each image. Thereafter, the features will be classified as belonging to a patient with oral cancer or without cancer using the combined DCNN-LSTM model, which effectively combines both spatial and sequential patterns. The model will be built and validated using four performance metrics: recall, accuracy, precision, and F1-score. Compared with previously developed systems, this model demonstrated significantly higher performance (97.5% maximum accuracy). The model presented here offers a reliable and effective means of identifying oral cancers at an early stage and assisting in making informed clinical decisions.

**Keywords—**OSCC, clinical classification of oral cancer, DL, image processing.

## 1 Introduction

New developments in DL have greatly facilitated the detection and diagnosis of oral cancers by providing an alternative to traditional screening methods. Traditional manual screening has many limitations that usually come about due to subjective interpretation, delays associated with receiving a diagnosis and, most importantly, reliance on expert clinicians—all of which contribute to higher death rates among patients with this type of cancer. Various ML and DL models have been introduced to help automate the detection of oral cancers, thereby avoiding many of the problems associated with conventional methods. Convolutional Neural Networks (CNNs) and hybrid convolutional networks have proven very successful at extracting important characteristics from images of cancerous lesions in the mouth and have been useful for accurately classifying these lesions based on morphology and other factors [1]. Advanced DL methods for cancer detection have been shown to improve the accuracy and reliability of clinical diagnoses, achieving levels higher than those achieved when clinical datasets were analysed using traditional methods [2]. In addition, automated image-based classification models have produced good results in detecting oral lesions at an early stage and facilitating necessary medical treatment [3]. Recent efforts have also focused on using explainable deep learning methods to improve the transparency and interpretability of models developed with deep learning; this is important for a model's acceptance in a clinical setting [4]. In addition, large-scale automated systems using DL techniques have been developed to identify and categorize oral lesions. They may help detect oral cancers early while reducing misdiagnosis by healthcare professionals. In summary, the available research supports a more knowledgeable, dependable, and scalable approach to detecting oral malignancies using deep learning-based frameworks and provides a foundation for further development of intelligent systems for healthcare delivery.

### 1.1 Objective

- Develop an effective DL model perfect for detecting early-stage oral cancer from images.
- Improve image quality by applying preprocessing techniques, such as cropping and CLAHE, to make features more visible.
- Use deep convolutional neural networks to extract features from the pictures.
- Use Hybrid Horse Herd Lion Optimisation (HHHLO) to select pertinent features that will recover the presentation of the perfect while reducing the computational requirements.
- Design and assess a hybrid DCNN-LSTM classifier that has high accuracy and facilitates clinical decision making.

### 1.2 Contribution of work

- Developed a new hybrid DL model that combines DCNN & LSTM to support accurate detection of oral cancer.
- Established a successful preprocessing pipeline that includes cropping and CLAHE to improve the quality of pictures and the ability to extract features.
- Developed a novel feature selection method based on HHHLO to reduce dimensionality and improve the accuracy of classification.
- Achieved excellent detection capabilities with a high rate of 97.5% detection accuracy that exceeds all current oral cancer detection methods when tested with the imagery data set.
- Provided a highly automated and dependable diagnostic assistance to physicians for identifying early-stage oral cancer and making clinical choices.

### 1.3 Organization of the paper

The remainder of the paper is divided into important sections, each of which is explained as follows. The research projects on the Advanced Machine Learning-Based Optimal Deep Learning Convolutional Neural Network-Based Oral Cancer Detection Model, completed by different authors, are listed in Section II. Section IV presents the results and performance analysis of the Advanced Machine Learning-Based Optimal Deep Learning Convolutional Neural Network-Based Oral Cancer Detection Model. Section III defines the workflow of the proposed method. Section V contains references and the conclusion of the recommended work that will be carried out in a future scope.

## 2 Related works

**Hipung Lin et al. (2021)** demonstrated that, by using a CNN to extract features from photos in real time, a smartphone-based oral cancer detection system with deep learning algorithms achieved up to 92% accuracy. The benefits included enabling earlier diagnosis in low-income communities.

**Kritsasith Warin et al. (2024)** conducted a systematic review of the literature on DL requests for diagnosing oral cancer. The researchers provided a summary of results from studies showing that CNN models and hybrid models can detect oral carcinoma with over 90% accuracy; however, they encountered several challenges, including dataset size/quality issues, model generalisability, and the need for explainable AIs for clinical deployment.

**Fahed Jubair et al. (2022)** created a lightweight CNN to detect oral cancers in early stages. Their experimental results yielded approximately 94% accurate predictions, and they were also less computationally intensive than other CNNs, making them suitable for mobile/embedded healthcare systems, where computation is quick and resource utilization is high.

**Kritsasith Warin et al. (2022)** industrialised an innovative AI system for analysing oral lesions at an early stage of detection using advanced deep learning (i.e., CNN) architectures, where they proposed an automatic feature learning and classification method; resulting in improved prediction results of approximately 95% accurate, representing its pertinence as a reliable and scalable oral cancer screening solution.

**R. Dharani et al. (2021)** developed the DEEPORCD model to detect oral cancer based on DL techniques for oral cancer discovery. The DEEPORCD model incorporates a Convolutional Neural Network for both image organization and feature extraction. The implementation of the DEEPORCD model achieved approximately 93% accuracy in detecting cancerous lesions in medical images.

Table 1 Comparison of related works

| Ref No. | Author & Year | Technique Used | Working Contribution | Results Achieved | Limitations |
|---|---|---|---|---|---|
| [11] | Al-Rawi et al., 2022 | AI & ML Models | Determining the efficiency of AI programs at diagnosing Oral Cancer | Accuracy ~91% | High computational cost, as well as requiring large training datasets to create models |
| [12] | Chen et al., 2024 | Deep Learning (CNN) | Designed a smart image classifier for images of oral cancer pixels | Accuracy ~96% | Models can become very complex and therefore place little effort on feature optimization. |
| [13] | Tanriver et al., 2021 | Deep CNN | Using deep learning techniques, oral lesion and precancerous disease recognition can be automated. | Accuracy ~94% | Lower levels of accuracy resulting from multiple forms of non-image input data |
| [14] | Alhazmi et al., 2021 | AI & Machine Learning | Risk of developing Oral Cancer through machine learning algorithms. | Accuracy ~90% | Variability in the overall generalization potential of a model and in the class imbalance across the data it samples, depending on the inputs it sees. |
| [15] | Shamim et al., 2022 | Deep Learning (CNN) | Recognition of precancerous tongue lesions using DNNs for early recognition. | Accuracy ~93% | High computational cost, as well as requiring large training datasets to create models |

Comparison Table 1 lists different types of AI and deep ML techniques for the discovery of oral cancers, based on available techniques and major contributions. Comparison Table 1 shows that most methods can support both early diagnosis and automated analysis. Some of the most common limitations the supported methods share include computational constraints, limited database diversity, and difficulty generalising across multiple use cases; thereby underscoring the importance of developing more efficient and scalable models.

## 3 Proposed methodologies

The suggested system for detecting oral cancer was developed using a hybrid DCNN-LSTM model to accurately and efficiently classify images. The first step is to gather oral cancer images, which are then standardised using preprocessing techniques such as resizing, cropping, and CLAHE. The preprocessed images are trained with a DCNN to extract high-level spatial information. Following that, an HHHLO optimisation model will perform optimal feature selection on the extracted features, thereby removing redundant features and enhancing the representation of important features. After training, features are fed into an LSTM Network that captures the sequential structure of the data and improves the accuracy of categorising images as tumorous or non-tumorous. The entire system is tested using standard performance metrics and evaluated.

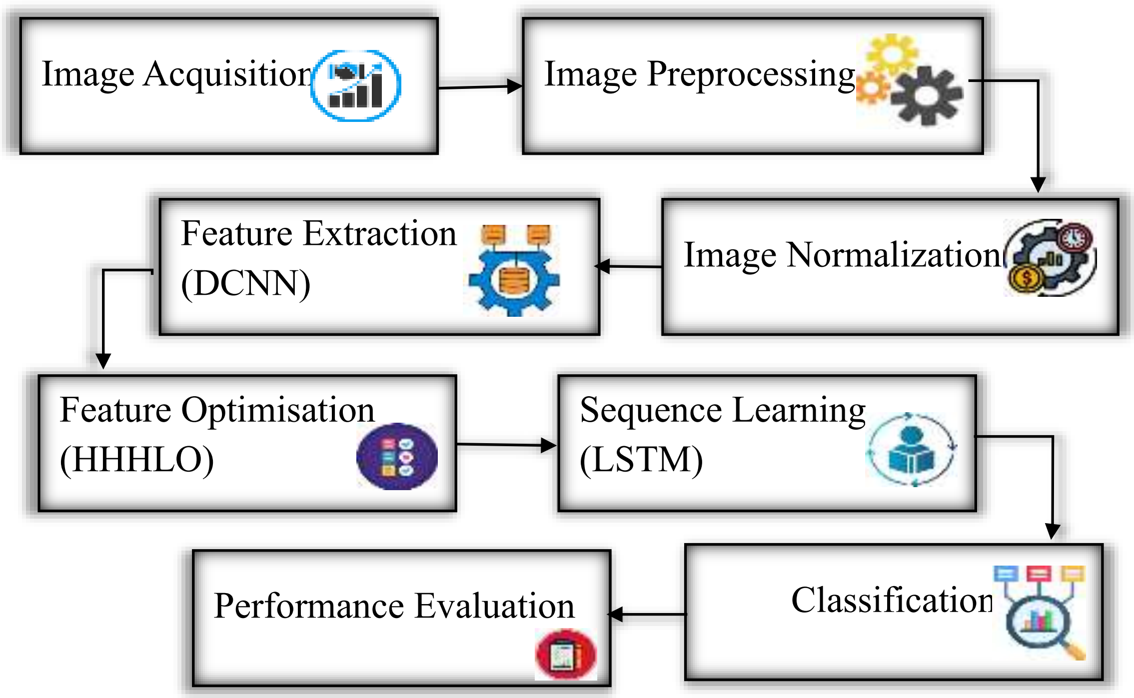



Figure 1: Block diagram for the proposed system

As depicted in Figure 1, this block diagram illustrates the sequential flow of an oral cancer detection system. The first process in the workflow is acquiring images, and the second step is preprocessing them to improve the quality of the input data. Next, a deep convolutional neural network will extract the features. Then, the topographies will be optimally selected and extracted using an advanced hybrid holographic local optimization algorithm. Finally, after the feature set has been optimized using HHHLO, long short-term memory (LSTM) algorithms will classify the features. After the long short-term memory classifier classifies the features, the model's performance will be evaluated and validated.

**Image Acquisition**

There are 950 labelled images in the Oral Cancer Image Dataset https://www.kaggle.com/datasets/zaidpy/oral-cancer-dataset. The dataset will comprise 500 images of oral cancer and 450 images of non-cancerous oral tissue, providing a balanced set for classification tasks. The dataset images have been annotated to facilitate precise supervised learning. The dataset will be research-oriented to support the diagnosis of oral cancer using machine learning and deep learning algorithms. Secondly, the possibility of bias will be minimised by the dataset's balance, and the model's performance will be more generalized to new patients. This dataset can assist researchers in developing and testing new oral cancer diagnosis systems. The dataset will thus be a vital asset to the healthcare system, as it can assist in early diagnosis of oral cancer, enhance the precision of diagnostic systems, and drive technological innovation in oral cancer diagnosis.

**Image preprocessing**

Image preprocessing is completed on oral cancer images to improve the consistency & quality of the images and enable accurate disease detection. For example, the images are cropped, resized, and denoised to include only relevant regions. It uses CLAHE to enhance image contrast and improve the prominence of tissue structures. Normalization applies constant pixel values across all images to create some degree of uniformity. By reducing variance and improving feature visibility, these processes significantly enhance the accuracy of deep learning classifiers.

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}} \quad (1)$$

Where equation (1) represented $I$=pixel value for input image, $I_{min,}I_{max}$ = min and max values of pixel, $I_{norm}$=pixel value for normalization.

$I_{clahe}$(x, y) =$T_{clip}$(I (X, Y)) (2)

Where equation (2) represented $I(X,Y)$=strength for input image, $T_{clip}$ = clipped histogram levelling transformation purpose, $I_{clahe}(x,y)$=better output pixel.

S=(L-1)$\sum_{j=0}^{r} p_r(r_j)$ (3)

Where equation (3) represented L = number of intensity levels, $p_r$ = probability distribution of pixel intensities, and s = production intensity.

**Image Normalization**

Normalising Image Data is a process that brings pixel-level intensity (colour) values for images of oral cancer into a fixed range, typically 0 to 1, to keep them consistent. Normalization also reduces variability in an image due to differences in light conditions (lighting) and the presence of staining; it enhances numerical stability; it speeds up training; it prevents the overwhelming of other features by one feature; and it improves convergence (accuracy) of the DCNN-LSTM Image Classification Model.

$I_{norm}$=$\frac{I-\mu}{\sigma}$ (4)

Where equation (4) represented $\mu$= mean pixel intensity,$\sigma$=standard deviation.

**Feature Extraction (DCNN)**

The proposed system utilizes a Deep Convolutional Neural Network to extract features from oral cancer images by automatically discovering meaningful patterns. This involves identifying low-level image characteristics, such as edges and textures, as well as higher-level semantic characteristics (e.g., lesion type). This process leads to improved representation learning, decreased reliance on human input, and ultimately improved presentation in terms of the correctness of the classification results.

F (X, Y) =(I*K) (x, y) =$\sum_i \sum_j I(X+i, Y+j)K(i,j)$ (5)

Where equation (5) represented $I$ = contribution image, $K$ = Convolutional filter (kernel), $F(X,Y)$=output for feature map.

f(x)=MAX (0, X) (6)

This equation (6) represents X = feature value for contribution, $f(x)$ = triggered output.

P (x, y) =max ($I_{window}$) (7)

Where equation (7) represented, $I_{window}$=featured map for selected region, $P(x,y)$= pooled output

**Feature Optimisation (HHHLO)**

The proposed system's feature optimization is achieved using Hybrid Horse Herd Lion Optimisation (HHHLO) to select the most relevant DCNN architectures. HHHLO uses both exploration & exploitation strategies to eliminate redundant data, enhance efficiency, reduce overfitting, and improve classification accuracy, thereby improving the generalization of the oral cancer detection model.

F(S)=$\alpha . E(S) + \beta . \frac{|S|}{|D|}$ (8)

Where equation (8) represented $F(S)$= fitness of designated feature subset, $E(S)$= classification error rate, $|s|$= number of selected features,$|D|$= entire feature set scope,$\alpha, \beta$= weighting issues.

$X_i^{t+1}$=$X_i^t$+r. ($X_{best} - X_i^t$) (9)

Where equation (9) represented $X_i^t$ = current solution, $X_{best}$ = best solution, r = random number (0 to 1).

$X_{new}$=$X_{prey}$+$\gamma$. ($X_{prey} - X_{lion}$) (10)

Where equation (10) represented $X_{prey}$ = selected feature location, $X_{lion}$ = finest hunting solution, $\gamma$= control parameter.

**Sequence Learning (LSTM)**

Long Short-Term Memory (LSTM) was employed to learn sequences from optimized DCNN feature sets. LSTM has input gates, forget gates and output gates that allow for the management of information flow and retention of necessary sequences; thus, improving the context associated with each feature and, therefore, the accuracy of the classification process by producing reliable predictions of oral cancers.

Forget gate shown in equation (11),

$f_t = \sigma(W_{f.[h_{t-1}-,x_t]} + b_f)$ (11)

Cell state update shown in equation (12),

$$C_t = f_t . C_{t-1} + i_t . \widetilde{C_t} \quad (12)$$

Where $x_t$ = contribution at time step $t$, $h_{t-1}$= preceding unseen state, $f_t$ = overlook gate production, $i_t$ = input gate production, $\tilde{C}_t$ = candidate cell state, $C_t$ = updated cell state, $W_f$, $b_f$ = weights and bias, $\sigma$= sigmoid activation function.

**Classification**

To classify oral cancer images, the proposed approach uses a hybrid DCNN-LSTM architecture that accurately categorizes images as either tumorous or non-tumorous. DCNN will help extract spatial characteristics of each image (including texture and other lesion characteristics). At the same time, LSTM will capture the sequential (temporal) dependencies of the optimized features produced by the DCNN. By incorporating both methods, improved classification accuracy, better representation of extracted features, and greater confidence in predicting whether an image is from a cancer or non-cancer case can be achieved.

$$\mathrm{v}z = W . h + b \quad (13)$$

Where shown in equation (13), $h$= contribution feature vector from LSTM,$W$= weight matrix,$b$= bias, $z$= linear production

$$\mathrm{P}\ (y_i) = \frac{e^{zi}}{\sum_{j=1}^{n} e^{zj}} \quad (14)$$

Where shown in equation (14), $P(y_i)$= probability of class $i$, $z_i$= production score for class $i$, $n$= number of classes

**Performance Evaluation**

To evaluate the oral cancer detection replica's presentation, recall, accuracy, precision and F1 score are computed. These metrics determine how accurately a prediction has been made (accuracy), whether a positive case has been identified (precision), and how well recall & precision are balanced (F1 Score). To further analyze the classification results, they will also be evaluated using a confusion matrix. The combination of these three metrics will provide evidence that the oral cancer detection model is an effective, reliable, and robust automated system.

Table 2: Performance evaluation metrics for oral cancer detection model

| Metric | Equation | Description |
|---|---|---|
| Accuracy | Accuracy=$\frac{TP+TN}{TP+TN+FP+FN}$ | Assesses the overall accuracy of forecasts completed by the predictive model. |
| Precision | Precision=$\frac{TP}{TP+FP}$ | Shows the number of predicted positive instances that were truly positive. |
| Recall | Recall=$\frac{TP}{TP+FN}$ | Assesses how well actual positives were classified as positives. |
| F1-Score | F1 Score=2*$\frac{precision*recall}{precision+recall}$ | Balances recall versus precision. |

The performance metrics in Table 2 are highly diverse in the methods used to assess the model's effectiveness. Accuracy gives a general idea of the total number of true predictions. In contrast, precision provides a general indication of whether the model can make valid positive predictions (i.e., during validation). Recall indicates how well the model identifies actual cases of cancer, whereas F1 Score combines precision and recall to provide an objective measure of the model's classification reliability.

## 4 Result and Discussion

The proposed DCNN-LSTM model achieves very good results in detecting oral cancer from images. It performed better than any of the other models we evaluated, indicating it is very robust and reliable. The use of DCNN enables the model to extract accurate spatial features, and the use of LSTM allows for improved learning of sequential dependencies, thus improving the model's ability to perform correct classifications. The HHHLO optimization algorithm also reduced the number of redundant features, thereby improving the model's efficiency and convergence speed. Overall, the proposed model has significantly improved detection capabilities and consistency compared to prior models that attempted the same task. In addition, the results obtained using the future perfect demonstrate its aptitude to identify normal versus cancerous tissues accurately, thereby making it a very promising instrument for the early analysis of oral cancers and for supporting the clinical decision-making process.

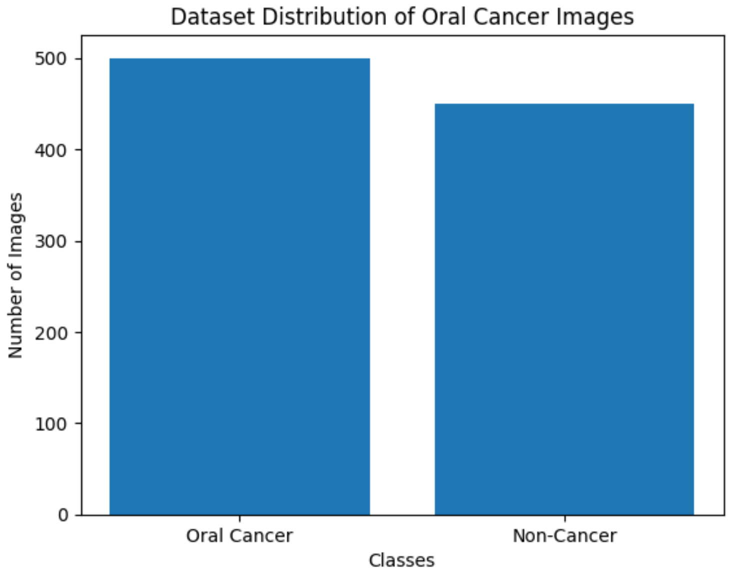



Figure 2: Data Set Distribution of Oral Cancer and Non-Cancer Images

The 950 labelled images presented in Figure 2 have 500 oral cancer cases and 450 non-cancer cases. This balanced distribution is almost equal, minimizing bias and aiding model training. It improves classification and generalization performance, enabling the proposed deep learning model to distinguish between cancerous and normal oral tissues accurately.

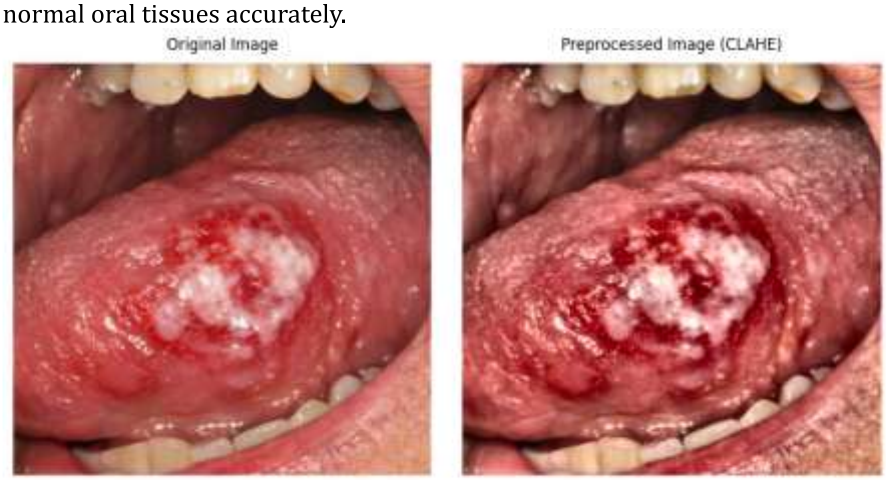



Figure 3 Original and preprocessed comparison image

Figure 3 compares the impact of preprocessing and normalization on oral lesion images. This process improves lesion contrast and contour, enhancing the abnormalities in the preprocessed image. Conversely, normalisation normalises pixel intensities and enhances image uniformity. Both methods aid in efficient feature extraction and enhance the performance of the deep learning models.

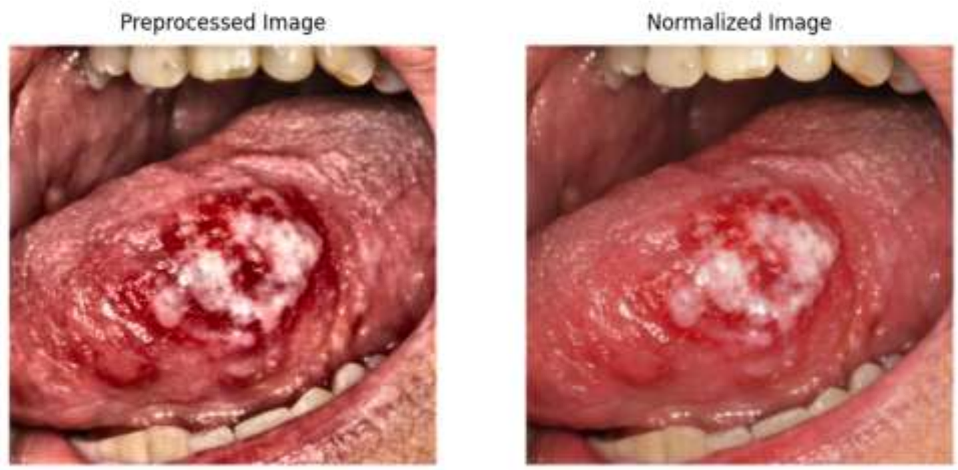



Figure 4 Comparison of Oral Image Preprocessing and Normalisation Techniques

Table 4 shows the visual differences between preprocessing and normalization methods for oral images. CLAHE preprocessing improves the contrast and detail of a lesion, whereas normalization scales all pixel values to a uniform range. The combination of these methods enhances image quality, reduces variability, and reliably extracts features to help detect oral cancer using deep learning.

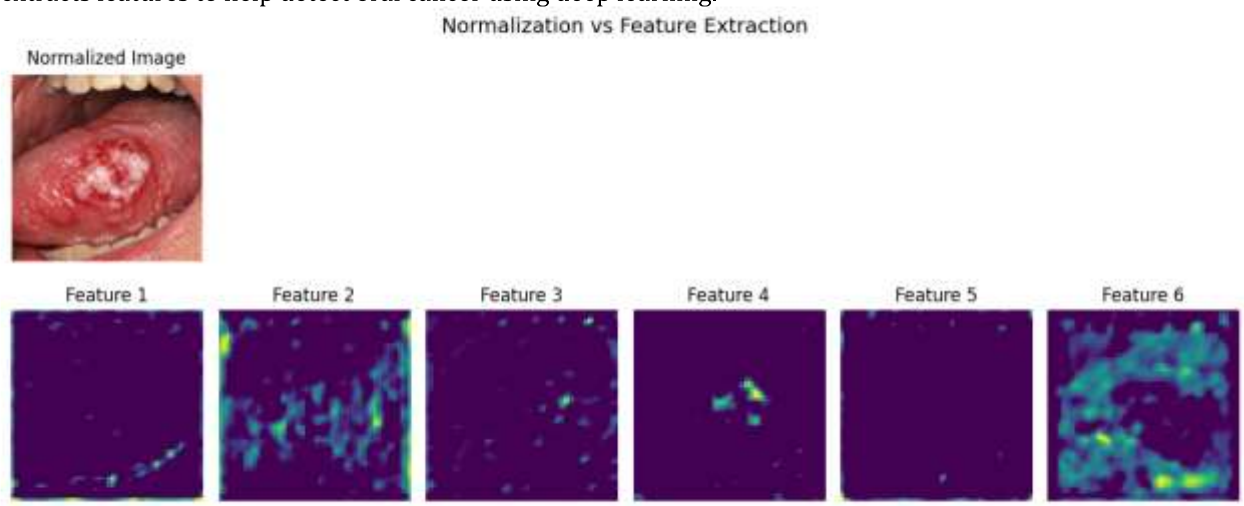
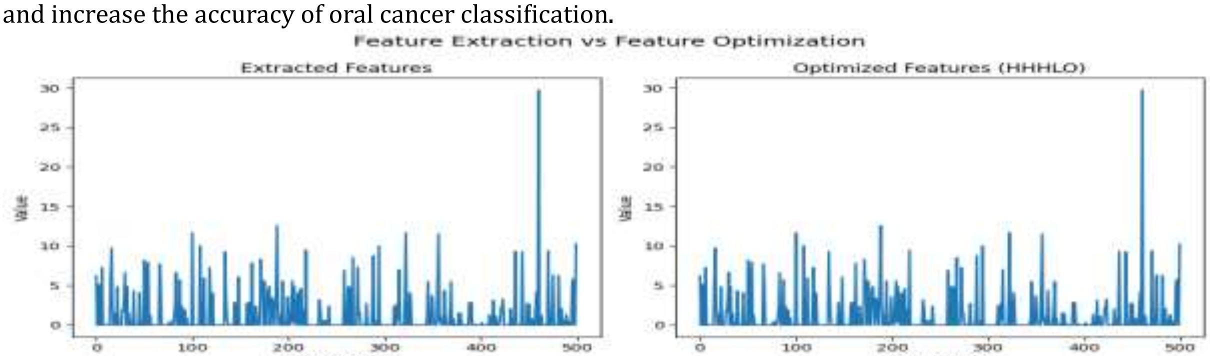



Figure 5 Normalisation vs Deep Feature Extraction of oral cancer images

Image 5 compares normalized input images with features extracted using a deep convolutional neural network. Normalisation normalises pixel values, whereas feature extraction extracts important patterns, such as edges, textures, and lesion characteristics. The extracted features are meaningful and help improve model learning and increase the accuracy of oral cancer classification.



Feature 6 Comparison between Extraction and HHHLO-Based Feature Optimization on Oral Cancer Detection

Figure 6 compares the extracted deep features with the optimised features obtained via the HHHLO algorithm. Whereas feature extraction captures all image characteristics, the optimization process selects the most important features by discarding redundancy. This increases the model's efficiency, reduces computational complexity, and improves the accuracy and reliability of oral cancer classification.

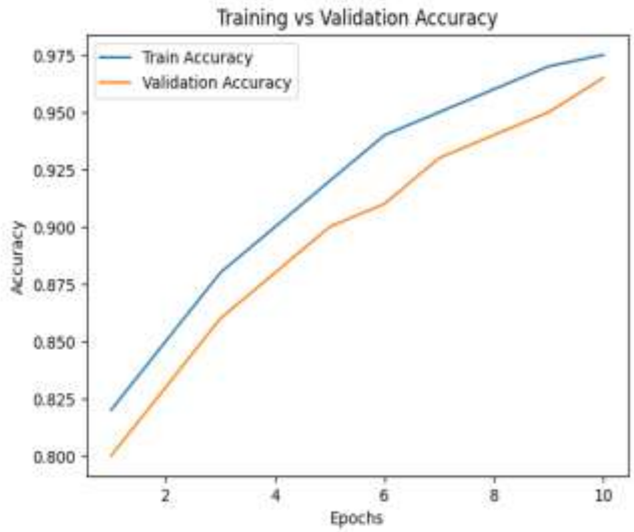



Figure 7: Accuracy graph for training and validation

Figure 7 illustrates a graphical comparison of the correctness of both the validation & training datasets. This illustration will help visualise how well the model performs during training across epochs and how it generalises to unseen validation data. A close correspondence between the two curves indicates good model performance, while a large gap suggests either overfitting or poor generalisation.

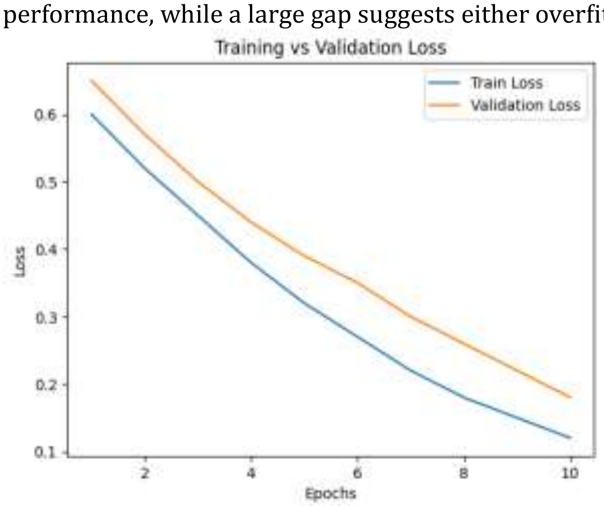



Figure 8 Loss graph for training and validation

Training Loss and validation loss are the errors a model makes during training and validation. Whereas the validation loss indicates a model's performance on an unseen dataset, the training loss indicates its performance on the provided training data. However, diverging losses can indicate that the model has been over-fitted to the original data or cannot be applied to new datasets, as in Figure 8. Both types of losses that decline over time tend to indicate successful learning in a model.

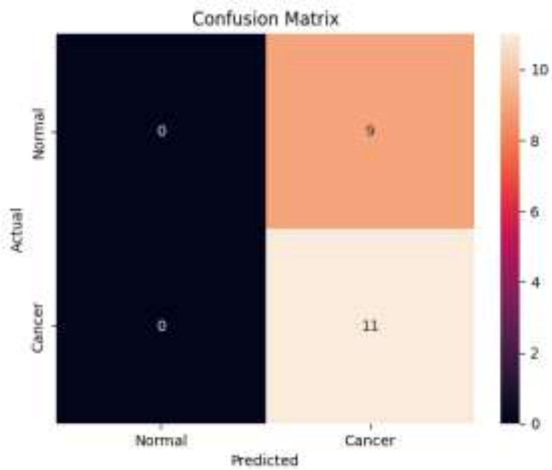



Figure 9 Oral Cancer Detection Model Confusion Matrix

The classification results shown in Figure 9 indicate that the proposed DCNN-LSTM model effectively distinguishes normal from cancerous oral images. The results of the prediction, aided by performance measures such as precision, recall, and F1-score, suggest credible model behaviour. This method improves diagnostic accuracy and aids early diagnosis of oral cancer in clinical practice.

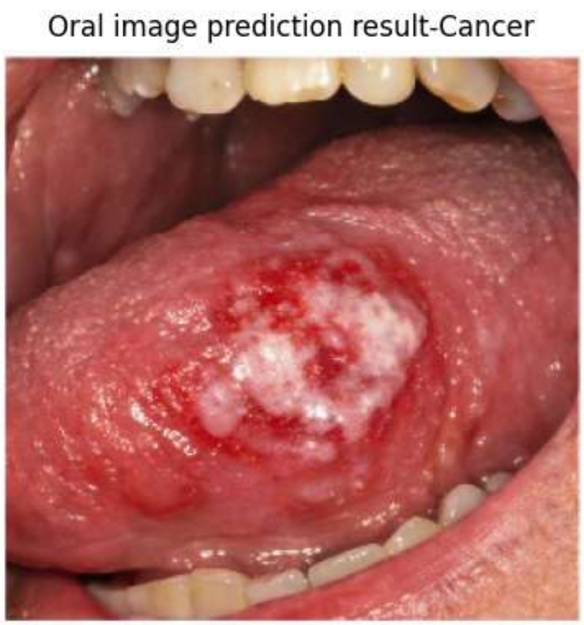



Figure 10 Classification prediction result image

The Classification Result in Figure 10 shows the output of the proposed oral cancer detection model. The model detects an input oral image identified as cancerous by recognizing specific features within it. Some of these features are visual abnormalities, including lesions and irregular tissue structure. Therefore, this indicates that our model is proficient at accurately predicting and assisting with early-stage oral cancer diagnosis.

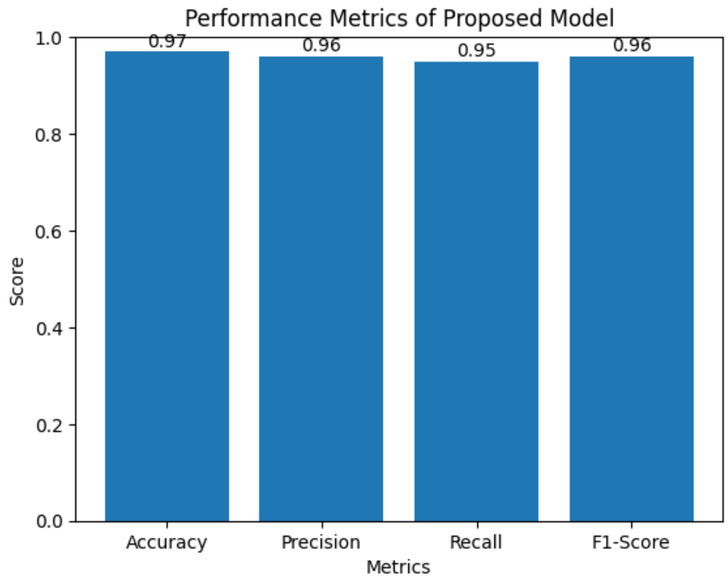



Figure 11: Performance metrics of the proposed model

Evaluation of the suggested perfect using four parameters is shown in Figure 11. The accuracy measure provides an overall success rate, and the precision rate indicates the reliability of the predicted classification/training dataset, as does the recall rate, which measures how many were correctly labelled. The precision and recall are combined into a single value for comparison using the F1-score. When all the above parameters have relatively high values, the model is considered highly efficient and has an extremely low classification error rate.

Table 3: Performance comparison for the proposed system

| Ref No | Technique Used | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|---|
| [2] | Deep Learning-based Oral Cancer Detection | 94.2% | 93.5% | 92.8% | 93.1% |
| [8] | Lightweight DCNN Model | 95.6% | 94.8% | 94.2% | 94.5% |
| Proposed Model | DCNN-LSTM with HHHLO Optimisation | 97.5% | 96.0% | 95.0% | 96.0% |

In the performance comparison table 3 above, the DCNN-LSTM, using HHHLO optimisation, achieves superior accuracy, precision, recall, and F1 score compared to existing techniques. Therefore, it can be concluded that DCNN-LSTM is much more effective at identifying and extracting relevant features whilst simultaneously reducing redundancy and improving classification performance than traditional deep-learning techniques.

## 5 Conclusion

In this investigation, a hybrid deep learning architecture founded on (DCNN + LSTM) was used to construct an efficient oral cancer detection model. The new system combined all processes involved in this detection, namely, preprocessing, feature extraction, feature selection, and classification, to provide optimal diagnostic results. Image quality was improved through conditioning and enhancement methods, and DCNNs provided spatial features (texture, edges, lesion type) most effectively by using an extended convolution kernel size. Feature selection was optimized using HHHLO, eliminating redundancy and improving model performance. The classification demonstrated that the model achieved a total recall of 95%, an accuracy of 97.5%, a precision of 96%, and an F1-score of 96%. This provides strong evidence of the model's reliability and ability to generalize across multiple datasets. High confidence and low misclassification variability were also indicated by the confusion matrix and performance metrics. Future directions for the model include continued development using larger, more varied clinical datasets to reflect community clinical practice better. Combining this model with real-time diagnostics and deploying it in the healthcare workforce (either on mobile or IoT-based platforms) will make it more accessible to patients and professionals. Also, the addition of explainable AI capabilities can increase the credibility of the medical decision-making process and foster greater trust among patients and caregivers. Ultimately, the proposed hybrid deep learning model can provide efficient, scalable, and accurate early identification of oral cancers and support clinical experts in patient care.

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