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DCGANOCIS: Convolutional Generative Adversarial Networks Based on Oral Cancer Identification System

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Abstract: This paper presents a novel feature extraction model for accurate oral cancer detection using a combination of Modified Deep Convolutional Generative Adversarial Networks (MDCGAN) and Convolutional Neural Networks (CNN). The primary objective is to classify input Oral Cavity Squamous Cell Carcinoma (OCSCC) images as healthy or sick. The proposed approach involves image enhancement, where the input image is resized, contrast-enhanced, and converted from RGB to YCbCr color space using the Improved CLAHE method. The main novelty of this work lies in the deep learning-based feature extraction model, MDCGAN, which differs from traditional GANs in its use. In the proposed MDCGAN model, the Generator (G) part is employed to enhance the number of samples of each image in the dataset, thereby increasing the size of features and improving the accuracy of predictions. In contrast to conventional GANs, the Discriminator (D) part is replaced with a Modified Convolutional Neural Network (MCNN). The findings demonstrate that the proposed method outperforms existing approaches, achieving remarkable results during the testing phase with 97.26% classification accuracy, 98.96% precision, 94.18% recall, and 96.34% f-measure. The success of the oral cancer prediction depends on the quantity and quality of derived features from OCSCC images, making MDCGAN a highly recommended model for image classification applications compared to traditional deep learning approaches. In summary, the paper introduces a novel approach for oral cancer detection, combining MDCGAN for feature extraction and CNN for classification. The method showcases superior performance over existing techniques, emphasizing the importance of the derived features' size in achieving higher accuracy. The innovative use of GANs for feature extraction and MCNN as the Discriminator leads to improved oral cancer prediction accuracy, making MDCGAN an effective choice for such image classification tasks.

Keywords: *Oral Cancer, Deep Learning, Classifiers, CNN, MDCGAN, DCGAN*

1. Introduction

More than 90% of oral malignancies are oral squamous cell carcinomas (OSCC), a heterogeneous group of cancers originating from the mucosal lining of the mouth cavity [1, 2]. Globally, OSCC ranks as the sixth most prevalent subtype of head and neck squamous cell carcinoma (HNSCC) [4]. Each year, approximately 657,000 new cases are identified, leading to over 330,000 deaths, with South Asian countries experiencing notably higher OSCC rates. India bears the majority of cases, accounting for almost one-third, despite Pakistan having the highest and second most common malignancies in both men and women [5]. Risk factors for OSCC include alcohol consumption, smoking, poor dental hygiene, HPV exposure, genetic factors, lifestyle choices, ethnicity, and geography. Early detection of OSCC is crucial to implement successful treatment strategies, impede rapid progression, and reduce mortality and hospitalization rates [6]. However, the prognosis for OSCC remains poor, with a 50% cure rate [7, 8]. Histological analysis of clinical specimens under a microscope remains the primary method for detecting OSCC [9, 10]. However, this approach can be laborious and prone to inaccuracies, limiting the effectiveness of diagnostic pathology approaches [11]. Hence, providing doctors with efficient diagnostic tools for OSCC evaluation and identification is vital. In recent years, research has seen significant advancements in applying artificial intelligence (AI)

to enhance clinical tests. The rise in diagnostic imaging has enabled researchers to explore AI applications in healthcare image processing, with deep learning (DL) effectively addressing various healthcare image processing challenges, including detecting aberrant images [14, 15]. Large-scale computer-aided diagnostic (CAD) procedures have been successfully developed and implemented for various cancer types, such as breast, lung, and prostate cancer [16-18].

Previous research on oral cancer diagnosis using deep learning (DL) has been limited. However, some studies have shown promising results. For instance, Dev et al. used Convolutional Neural Network (CNN) and Random Forest techniques to identify keratin pearls in oral histology images, achieving classification rates of 96.88% and 98.05%, respectively [19]. Similarly, Das et al. employed DL to classify oral biopsy images based on Broder's

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histological grading system, obtaining a classification accuracy of 97.5% using CNN [20]. In another study by Folmsbee et al., Active Learning (AL) outperformed Random Learning (RL) by 3.26% when categorizing oral cancer images into seven classes using CNN [21]. Additionally, Martino et al. explored various deep learning architectures like U-Net, SegNet, U-Net with VGG16 encoder, and U-Net with ResNet50 encoder to classify oral images into three groups (carcinoma, noncarcinoma, and nontissue). The upgraded U-Net with ResNet50 as the encoder demonstrated superior performance compared to the regular U-Net [22]. A more recent study by Amin et al. involved binary classification of oral disease images using feature extractors and enhanced Inception V3, VGG16, and ResNet50 networks [23]. These findings collectively highlight the potential of DL in oral cancer diagnosis, with various models showing promising results in different image analysis tasks. A deep learning approach was used to classify oral images as normal or abnormal, with an additional partitioning of diseased patches using the Distributed Affinity Propagation (AP) algorithm. The system effectively detected oral cancer with high accuracy, utilizing a small number of oral images in the research, despite early-stage manifestations being commonly misunderstood due to the lack of pain and mimicry with other lesions[29].

2. Methodology

Fig. 1 depicts the total system architecture for the discovery of oral cancer. Cancer tissue pictures are trained in an offline technique. The oral image input is pre-processed in the online process.Then; the features are derived from pre-processed image to find the canceraffected regions. After completing feature derivation process, the next process is to detect theoral cancer image using proposed deep learning classifier model featureEquations

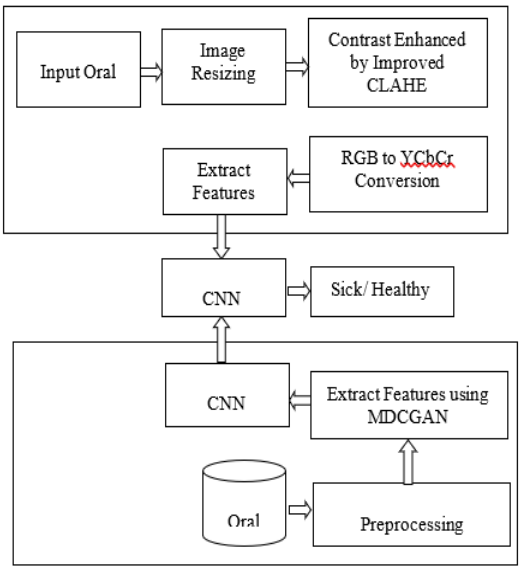


Fig 1. Overall architecture of DCGANOCIS

The suggested DCGANOCIS-based oral cancer detection model is divided into three stages: (i) image preprocessing, (ii) Future Extraction using MDCGAN and (iii) CNN-based oral cancer prediction. The three phases are discussed in detail in the following

2.1 Pre-Processing

This section provides the details of the preprocessing steps that are followed to prepare oral cancer images for further oral cancer feature extraction and identification steps. The oral cancer image preprocessing steps including image resizing, contrast enhancement andcolor space conversion.

(i) Image Resizing

Theinput OCCC imageis first resized from its original size to 227x227x3 size. This process is called image resizing.

(ii) Contrast Enhancement

The flow procedure below and the flowchart in Fig. 2 both present the entire algorithm for the contrast enhancement method.

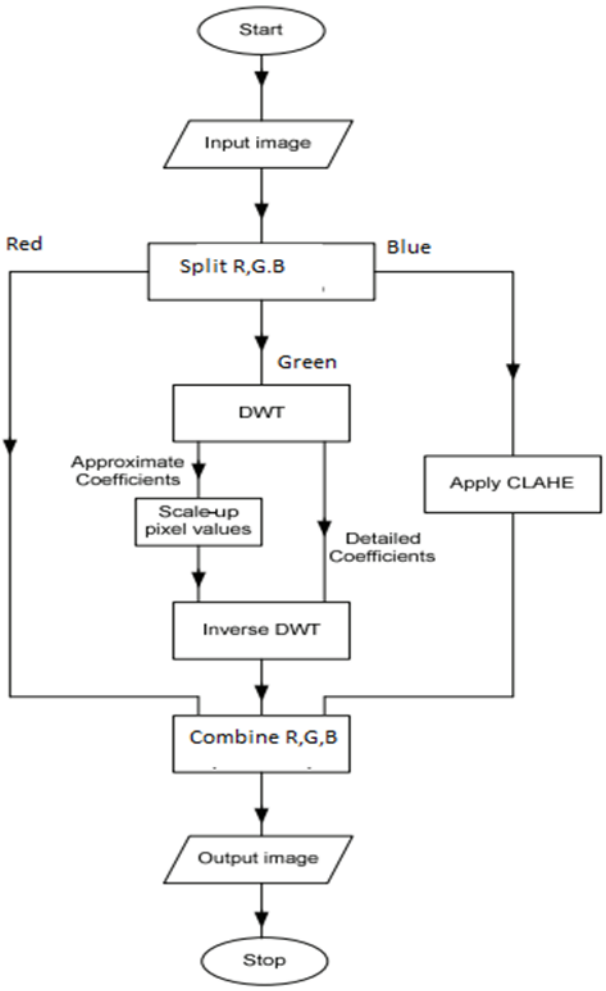


Fig 2. Improve CLAHE architecture

Algorithm step of Improved CLAHE

1) Open a scaled picture

2) Transform the Green component using Discrete Wavelet Transform (DWT).

4) Use the Inverse Discrete Wavelet transform to reconstruct Green.

5) Use CLAHE to improve the Blue component.

6) To create an upgraded RGB image, combine R, new Green, and new Blue components.

(iii) Color Space Conversion

In computer graphics, the red, green, and blue colour space is frequently utilised. The three-dimensional Cartesian coordinates system uses red, green, and blue as its three fundamental hues. It is an additive colour space with a 0 to 255 range for each component. The RGB colour space confronts numerous difficulties, such as changes in lighting. As a result, YCbCr colour space is created from RGB colour space. It employs the subsequent equation.

$$Y=0.412453R+0.357580G+0.180423B$$

$$Cb=0.212671R+0.715160G+0.072169B$$

$$Cr=0.019334R+0.119193G+0.950227B$$

2.2 Feature Extraction

Feature extraction is the procedure of transforming a picture into numeric data that may be analyzed while preserving the data in the real picture data set. This is the very important step in oral cancer prediction because it derives the most discriminating characteristics from the input image which is used for uniquely identify the oral cancer images. The accuracy of the oral cancer prediction depends on the size and quality of the derived features. If the size of features is increased the accuracy will be increased. To achieve this, a novel deep learning based feature extraction model (MDCGAN) is developed.

MDCGAN is developed by combing two deep learning models such as Generative Adversarial Networks (GAN) and Convolution Neural Network (CNN). This is shown in Fig.3. Generally, GAN is used to enhance the number of image in the dataset. But in our approach GAN is used for extracting deep features. Traditional GAN consists of two parts one is Generator (G) and the other part is Discriminator (D). G is used for producing fake images and D is used for identifying real or fake images. But in our proposed MDCGAN model the Generator(G) parts work same as traditional GAN. This parts is used to enhance the no of samples of each images in the dataset. If the size of features is increased the accuracy will be increased. The size of features depends on the no images in the training dataset. So Generator(G) parts increase the no images in the dataset to enhance the accuracy of prediction. But the Discriminator (D) part in traditional GAN is replaced with Convolution Neural Network (CNN).

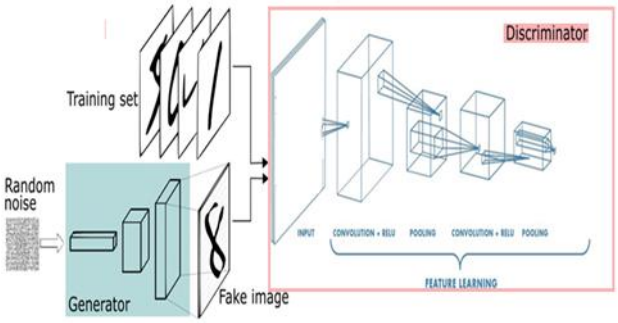


Fig 3. MDCGAN architecture

Traditional CNN have three layers. The first layer is convolution layer. It is used for extracting / enhancing features. The second layer is pooling layer which is used for reducing the amount of features retrieved from the convolution layer. Generally, max or average pooling are used in traditional CNN. But in our proposed model, to get unique discriminating features Fuzzy Particle Swarm Optimization (FPSO) method is used instead of max or average pooling. As a result, the suggested approach increases accuracy while decreasing time complexity. In Fig. 4, this is depicted.

FPSO is created on the subsequent Equation 1,

$$FPSO\ (p) = \sum_{k=1}^{n}\sum_{i=1}^{c}[\tau_{ik}]^m \|y_k - W_i\|^2 \quad (1)$$

where, m>1 is a real digit, W_i is the cluster centre of i, y_k is the vector division of k. It is calcuated based on Equation 2.

$$W_i = \frac{\sum_{k=1}^{n}[\tau_{ik}]^m y_k}{\sum_{k=1}^{n}[\tau_{ik}]^m} \quad (2)$$

$$[\tau_{ik}]^{(t+1)} = \left[\sum_{j=1}^{c}\left(\frac{\|y_k - W_i^{(t)}\|^2}{\|y_k - W_i^{(t)}\|^2}\right)^{\frac{1}{m-1}}\right]^{-1} \quad (3)$$

Where c = 1, 2, ...n, $\|y_k - W_i\|^2$ - Euclidean distance among y_k along with W_i, as well as $[\tau_{ik}]^{(t+1)}$ - degree of membership of element k belongs to ith cluster

The final layer is fully connected layer which is used for training and predicting the oral cancer image. But in work we eliminate the third layer. Because we need only features.

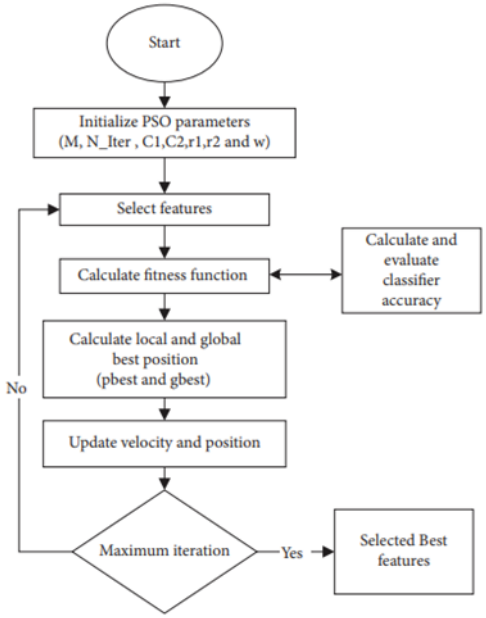


Fig. **4** FPSO architecture

2.3 Classification Using Proposed CNN

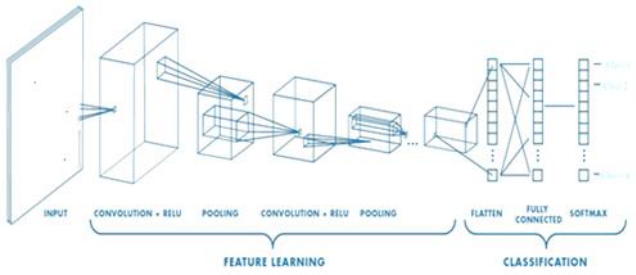
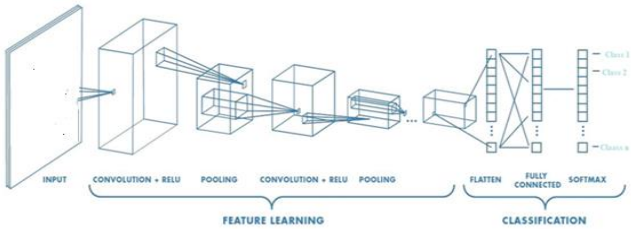


Fig 5. Proposed CNN architecture



The proposed CNN architecture consists of eight convolution layers, four pooling layers, four dropout layers, two flattening levels, and two fully connected layers, as detailed in Table 2. The convolution layers are responsible for detecting local patterns and mapping features from the previous layer to the CNN feature map. At the end of the convolution layer, the images are processed through perceptron's and transformed into feature maps. The depth of these feature maps depends on the number of filters in each layer, resulting in multiple filters. Each filter takes a specific aspect out of the source image. Each pixel is convolved three times using the proposed CNN's convolution layers, which use the input images as a matrix. The feature map of the photos is then calculated using the horizontal stride.

In the pooling layer, the maximum value is determined and the matrix size is minimized. A dropout layer is used to update the hidden layers according to the training stage, preventing overfitting. The feature map is flattened during the procedure so that it can be transferred to the fully linked layer as a one-dimensional array. The fully connected layers then categories the labels as healthy or unhealthy.

Table 1: Proposed CNN Layer Information

Layer's Name	Type/Stride	Filter
Input	Image Input	--
C1	Convolution	3 x 3 Conv 32
C2	Convolution	3 x 3 Conv 32
P1	MaxPool	--
D1	Dropout	--
C3	Convolution	3 x 3 Conv 32
C4	Convolution	3 x 3 Conv 32
P2	MaxPool	--
D2	Dropout	--
C5	Convolution	3 x 3 Conv 32
C6	Convolution	3 x 3 Conv 32
P3	MaxPool	--
D3	Dropout	--
C7	Convolution	3 x 3 Conv 32
C8	Convolution	3 x 3 Conv 32
P4	MaxPool	--
D4	Dropout	--
FC1	Fully connected	256 x 9216
F1	Flatten	--
FC2	Fully Connected	3x256

In the pooling layer, the maximum value is determined and the matrix size is minimized. A dropout layer is used to update the hidden layers according to the training stage, preventing overfitting.The feature map is flattened during the procedure so that it can be transferred to the fully linked layer as a one-dimensional array. The fully connected layers then categories the labels as healthy or unhealthy

4. Results and Discussions

4.1 Data set used

Data from an OSCC biopsy were obtained from the publicly available Kaggle [41]. The oral cancer dataset comprises healthy and sick patients. The model uses it to predict oral cancer, as shown in Fig. 5 and Table 2.

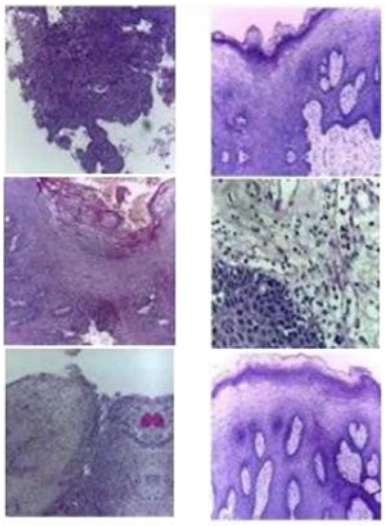


Fig 6. Sick and healthy from OSCC dataset

Table 2. Datasets

Classes	No. of Images
Sick (OSCC)	2510
Healthy	2434

4.2 Performance metrics used

There are numerous examination factors accessible to evaluate the performance of the prediction algorithms. This work simply takes into account the factors below.

i. Detection Accuracy

$$\text{Accuracy}=TP+TNTP+FP+TN+F \quad (7)$$

ii. Precision Rate

$$\text{Precision}=TPTP+FP \quad (8)$$

iii. Recall Rate

$$\text{Recall}=TPTP+FN \quad (9)$$

iv. F Measure

$$Fm=1+\alpha*\text{Precision}*\text{Recall}\alpha*(\text{Precision}*\text{Recall} \quad (10)$$

With the same layer settings of227 × 227 × 3, FPSO of picture dimension and pooling method, Table 3 displays the suggested results of the model training simulation settings for the different tested epoch counts.

Table 3. Model Training Simulations

No.of Epochs	Learning Rate	No. of Layers	Image Dimension	Pooling Method	Mini-Batch Loss
10	0.001	20	227X227 x3	FPSO	2.5464
20	0.001	20	227X227 x3	FPSO	2.3288
30	0.001	20	227X227 x3	FPSO	1.339
40	0.001	20	227X227 x3	FPSO	1.4738
50	0.001	20	227X227 x3	FPSO	0.2281

The performance of the suggested strategy in classifying oral cancer on the test and training datasets is detailed in Table 4. The outcomes are examined using various sizes of training and testing data. The experimental results showed that the suggested model has achieved accurate results for all sizes of training and testing data.

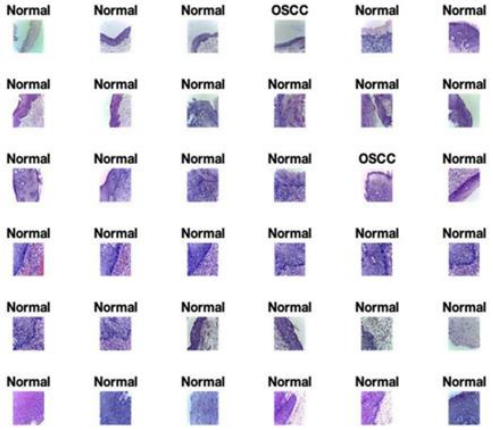


Table 4. Performance of both Test and Training Datasets

Training/ Testing	Class labels	Accuracy	Precision	Recall	F-score
90:10	Healthy	98.86	99	94.10	96.72
90:10	Sick	97.26	98.96	94.18	96.34
70:30	Healthy	96.75	96.89	91.99	94.61
70:30	Sick	95.15	96.85	92.07	94.23
60:40	Healthy	95.73	95.87	90.97	93.59
60:40	Sick	94.13	95.83	91.05	93.21
50:50	Healthy	94.83	94.97	90.07	92.69
50:50	Sick	93.23	94.93	90.15	92.31

Table 5. Comparison of Proposed Model

Work	Preprocessing Layer	Models	Accuracy	Error Rate
A.Alhazmi [26]	No	ANN	78.95%	21.05%
C.S. Chu[27]	No	SVM, KNN	70.59%	29.41%
R.A. Welikala[28]	No	RenEET101	78.30%	21.70%
Proposed	Yes	MDCGAN-CNN	93.23%	6.77%

Table 5 compares the proposed approach for predicting oral cancer involves utilizing transfer learning in combination with insights from prior studies. The effectiveness of the suggested model in relation to classification precision during the testing stage. The suggested model's classification accuracy and error rate during testing were 93.23% and 6.77%, respectively. The analysis's overall summary reveals a 12% improvement in classification accuracy over the previously proposed deep learning [28] and machine learning [26,27] models. In comparison to earlier research that has been published [26–28], the suggested model provides greater classification accuracy.

5. Conclusion

In this study, OSCC were used to identify malignant oral tissue from normal oral tissue using CNN's customised AlexNet. The proposed approach was appropriately and effectively analysed using the performance metrics Classification Accuracy, Precision, Recall and F1-measure. We can quickly assess the accuracy of the suggested model for the prediction of oral cancer using statistical performance measures. So, the accuracy and error rate for the suggested model were respectively 90.06% and 9.08%. The suggested model's specific layer procedures, dataset preprocessing methods, and training epochs are what provide it the highest accuracy achievement.The primary innovation of the suggested approach is the ability to create CNN networks during pandemic scenarios using a variety of CT images that are readily available. It is common knowledge that getting access to CT imaging during a pandemic could be challenging.

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Author contributions

Dharani, Revathy, Danesh, Deeptha and Preethi Parameswari contributed to the design and implementation of the research, the analysis of results, and manuscript writing.

Conflicts of interest

The authors declare no conflicts of interest.

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