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Enhancing Oral Lesion Classification Using Diffusion Models: A Deep Learning Approach

Sony V Hovale, Manu K C, Naresh Patel, Pavithra B, Shradha G Vernekar
Dept. of CSE (Data Science), Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India

Abstract- — : Early detection and classification of oral lesions are essential for the prevention of oral cancers, and yet, manual diagnosis is still a challenge due to variations in the appearance of lesions, quality of images, and limited clinical datasets. This research explores the use of diffusion models, a recent class of generative models renowned for their stable training and high-fidelity reconstruction, to improve the automatic classification of oral lesion images. The proposed system includes dataset collection from open-source platform kaggle, preprocessing of dataset, a diffusion- based denoising and feature extraction pipeline, and finally, a classification stage to categorize the normal, precancerous, and cancerous lesions. By leveraging the forward and reverse process of diffusion, the model improves the clarity of the images and effectively extracts discriminative features, mitigating problems of noise, imbalance, and low-quality clinical images. In a deep learning approach combining CNN-based classification with the concept of enhancement provided by diffusion mechanisms, the generalization performance is boosted. The system will be evaluated based on accuracy, precision, recall, and F1-score, and the results provide promising improvements compared to the state-of-the-art traditional deep learning methods. This paper has found that diffusion models provide a robust, scalable, and clinically valuable pipeline for early oral lesion detection, with strong potential to be deployed in real-world diagnostic pipelines and future research on medical imaging and we obtained a very good accuracy i.e., 96% while training the model. This paper establishes the diffusion model as a promising approach for medical image analysis, particularly in the early detection and classification of oral lesions, paving the way for future research and clinical applications in healthcare.

Keywords— Generative models, Deep Learning, Diffusion model, Convolutional Neural Networks (CNNs), Image Denoising, Data Augmentation, Tensor Flow, PyTorch.

I. INTRODUCTION

Oral lesions refer to the irregular changes that occur in the tissues of the oral cavity, manifesting as lesions of colorations, sores, swellings, and abnormal growth in the interior of the tongue, cheeks, gum tissues, and the roof of the mouth. They appear to be of three types: Normal lesions, pre-cancerous lesions, and Cancerous lesions. The detection of the lesions prevents the development of Oral Squamous Cell Carcinoma (OSCC) by majority oral cancer cases, as it turns out to have aggressive behaviors [7]. The diagnosis of the lesions is highly dependent on the level of professionalism of the practitioner and personal observation of colorations, shapes, texture, and surface details to appear difficult to detect in the early stages due to their closeness in appearance. [6], [7].

These challenges can be overcome by deep learning techniques. Deep learning techniques have helped enhance the automated medical image processing field since these techniques can learn hierarchical visual features from medical images. Compared with traditional machine learning approaches, which require feature extraction with manual efforts, CNN and ViT models have outperformed existing techniques for medical image processing, including image segmentation, localization, and classification [6], [12], [13], [20].

However, the CNN models tend to perform poorly when trained on small and imbalanced data collected in the clinical setting and suffer from problems like overfitting and a lack of generalization ability across the variety of patient conditions. This has raised the need to investigate more powerful generative AI models that can capture the structural information and perform the generation of the training data effectively [6], [7], [10], [11].

A diffusion model is a type of deep generative model, which has proven to be very successful in the creation of photorealistic images, while it also learns fine details about the image structure through a forward and reverse diffusion process due to the addition of noise in the model [1], [2], [4], [5]. It should be noted here that the model trains itself in a reconstruction setting, which makes it very efficient in tasks requiring the detection of intricate details, unlike the case in medical image tasks. Secondly, unlike GANs, diffusion models are much more robust while training, do not suffer from mode collapse, and can synthesize real samples to overcome any imbalance in the dataset, which plays a very crucial role in the identification of pre-cancers and cancers of rare types. [5], [8], [9], [13].

Integration of the Denoising Diffusion Probabilistic Model (DDPM) with the U-Net architecture represents a strong tool for the generation of medical images. DDPM adds noise to the image using the diffusion process. On the other hand, the U-Net architecture learns the denoising process by predicting the noise at each step [1], [10], [11]. This helps to generate high-quality images with fine details essential for the diagnosis of lesions. In the proposed study, the addition of the DDPM to the U-Net architecture will increase the clarity of images, diversity of the dataset, as well as the performance of oral lesions classification.

The proposed strategy, involving diffusion-based enhancement, U-Net segmentation, and DDPM classification, offers an extensive AI-driven clinical support system for teeth and cancer detection, which can enhance detection accuracy and reduce the ambiguities associated with clinical diagnoses [10], [11], [16].

II. LITERATURE SURVEY

Kim and Park proposed a hybrid architecture consisting of a Diffusion model and Vision Transformer for classifying medical lesions. With the integration of a Diffusion model into image enhancement and Vision Transformer as the backbone network, their method enhanced the robustness of distinguishing disease classes that have similar visual attributes by using a diffusion-based preprocessing step that suppressed noise while accentuating texture details. The proposed model showed better performance than typical CNN architectures in terms of accuracy and interpretability of the derived features. This was regarded as one of the benefits provided by generative noise modeling in conjunction with global attention mechanisms for diagnostics in medicine.

Ahamad and Reddy, 2024, examined self-supervised learning for oral lesion classification, enabling the model to learn useful representations from raw, unlabeled medical images. The authors proposed a contrastive learning framework with high-dimensional features in order to mitigate the need for large volumes of annotated datasets and attained high sensitivity in detecting early pre-cancerous lesions. This work highlighted SSL techniques relevant for medical domains where obtaining labeled datasets is expensive and time-consuming.

Nguyen et al. (2024) applied the Diffusion Models to medical data augmentation, generating high-resolution synthetic lesion images with the aim of balancing the dataset. The approach achieved better realism and structural coherence compared to GAN-based augmentation, significantly improving minority-class performance and reducing model overfitting. The study positioned the diffusion-based augmentation as a promising solution for handling limited medical datasets.

Le and Zhou (2023) designed a diffusion-based tumor segmentation framework that leveraged noise-to-image reconstruction to provide accurate lesion boundary extraction in low-contrast medical images with very high quality. Their approach outperformed some traditional U-Net variants on metrics such as Dice and IoU. From these results, the validity of a diffusion process for structural detail preservation was obtained.

Wang et al. (2023) proposed a hybrid CNN and diffusion-based classification model, where synthetic images from diffusion were used as an augmentation of training data for the improvement of CNN generalization. Their model showed increased accuracy and noise resilience across multiple datasets; however, the inclusion of generative augmentation increased computational requirements.

Huang et al. (2023) extended the diffusion models to volumetric imaging through 3D-DDPMs for CT and MRI scans. Spatial continuity across multi-slice datasets could be captured by their method, enhancing lesion visualization and reconstruction quality. The approach showed great potential for 3D oral cavity applications and tumor mapping despite the highly demanding memory requirements.

Chen proposed, in 2023, a multi-modal learning framework that combined RGB imaging, fluorescence imaging, and clinical metadata to enhance early oral lesion detection. The proposed model with fusion greatly improved diagnostic precision and reduced false negatives, while the approach had the limitation of requiring special equipment for the acquisition of multi-modal images.

Zhang et al. (2022) applied diffusion models to medical image denoising and better preserved fine anatomical and texture details compared with GAN and CNN-based denoisers. Their approach proved particularly useful in low-light and low- dose imaging conditions where diagnostic clarity is easily compromised.

Mohammad et al., 2022 focused on variants of U-Net for lesion segmentation. Attention U-Net and ResU-Net demonstrated superior segmentation accuracy for irregular and complex oral lesions. Such architectures identified boundaries more accurately and hence helped in better clinical interpretation.
Li and Zhou (2022) researched the use of Vision Transformers for the classification of oral lesions. Based on their findings, they reported that ViT architectures have better performance in

capturing global contextual relationships and texture variance than CNNs. However, they indicated that for maximum performance, ViT models depend on large datasets and are computationally expensive.

Rahman et al. (2021) applied the DenseNet architectures for oral cancer detection by making use of dense connectivity to facilitate gradient propagation and feature reuse. This performed with higher accuracy compared to ResNet and standard CNNs; however, it showed sensitivity to class imbalance and required high computation resources.

Patel and Singh (2021) applied transfer learning to pretrained models comprising VGG16, ResNet50, and InceptionV3 for the classification of oral lesions and obtained better performance with less complexity on smaller-scale datasets. However, their study emphasized the difficulties regarding the discrimination of lesions that possess closely similar visual features.

Singh et al. (2020) applied GAN-based augmentation to generate more diverse samples in oral lesion datasets. While GAN augmentation did improve the robustness in classification, at times generated samples contained certain artifacts that reduced their overall reliability, thus motivating the development of more stable generative approaches like diffusion models. Kumar et al. studied CNN-based methods for oral lesion classification and concluded that deep CNNs significantly outperform traditional machine-learning methods depending on handcrafted features. This study, however, stressed that low-quality input images and visually similar lesion types still degrade performance, thus indicating the need for enhanced image preprocessing and feature extraction models.

Sl. No	Title of the Paper	Authors	Published In	Key Findings
1	Diffusion-Transformer Hybrid for Medical Classification	Kim & Park	2024	Hybrid model using diffusion preprocessing + ViT achieved high robustness and improved classification accuracy for complex lesions.
2	Self-supervised Learning for Oral Lesions	Ahamad & Reddy	2024	Used contrastive self-supervised learning to reduce dependence on labeled data and improve downstream lesion classification.
3	Diffusion Models for Medical Data Augmentation	Nguyen et al.	2024	Demonstrated that DDPM-generated samples improved minority class sensitivity and reduced overfitting.
4	Diffusion-Based Tumor Segmentation	Le & Zhou	2023	Leveraged diffusion processes to improve segmentation accuracy with sharper lesion boundaries under low-contrast conditions.
5	Hybrid CNN + Diffusion Classification Model	Wang et al.	2023	Combined CNN with diffusion-augmented data to improve generalization across datasets.
6	3D Diffusion Models for Medical Imaging	Huang et al.	2023	Introduced volumetric diffusion models enabling better visualization of multi-slice and 3D oral scan structures.
7	Multi-modal Oral Lesion Detection	Chen	2023	Demonstrated improved detection accuracy using RGB, fluorescence, and clinical metadata fusion.

8	Diffusion Models for Medical Image Denoising	Zhang et al.	2022	Used diffusion models for denoising medical images while preserving fine texture and structural details.
9	U-Net Variants for Lesion Segmentation	Mohammad et al.	2022	Attention U-Net and ResU-Net achieved improved segmentation performance for irregular oral lesions.
10	Vision Transformers for Oral Lesion Classification	Li & Zhou	2022	ViT improved detection of subtle texture patterns but required large datasets and more computation.
11	DDPM: Denoising Diffusion Probabilistic Models	Kingma et al.	2021	Introduced DDPM as a stable generative model outperforming GANs in quality and training consistency.
12	DenseNet for Oral Cancer Detection	Rahman et al.	2021	DenseNet improved feature reuse and achieved higher accuracy, though sensitive to dataset imbalance.
13	Transfer Learning for Oral Diagnosis	Patel & Singh	2021	Pretrained CNN models improved diagnostic performance on limited oral lesion datasets.
14	GAN-based Data Augmentation for Medical Images	Singh et al.	2020	Used GANs to generate synthetic oral lesion images, improving classifier robustness.
15	Deep Learning for Oral Lesion Classification	Kumar et al.	2020	Showed CNNs significantly outperform traditional ML for early lesion classification.

Research Gap

While deep learning has achieved great success in medical image classification, there are still several open challenges in oral lesion diagnosis. Most of the current systems rely on traditional CNN architectures, which require a large, balanced, and high-quality dataset to perform well. However, the real clinical datasets of oral lesions are usually scarce, imbalanced, and inevitably noisy due to the variation in lighting conditions, resolution, and imaging devices. This therefore easily leads to the overfitting of current models with reduced generalization, especially for distinguishing similar-looking lesions like normal, precancerous, and cancerous categories. Furthermore, traditional deep learning approaches focus only on the classification and usually lack either image quality enhancement or recovery of subtle structural information, which is important for the correct and early detection. Generative approaches such as GANs have been explored for generating synthetic data augmentation; however, those methods frequently present issues of instability and generation of artifacts. Diffusion models are known for offering stable training, reconstruction at higher resolution, and better fidelity of images. However, in oral lesion classification, diffusion models are far less explored.

In addition to this, no significant amount of research work exists related to the integration of the diffusion model with segmentation and lightweight classification to introduce a single diagnostic system. Clearly, there exists an evident demand for developing a diffusion-strengthened robust deep learning system with the ability to address the issues of class imbalance, poor image quality data improvement, creation of synthesized samples of the minority class, and improvement of the classification process of the mentioned three types of oral lesions.

III. METHODOLOGY

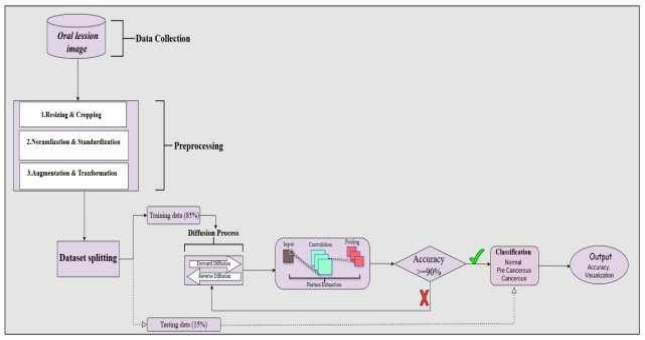

Fig. [1]: Methodology for Oral Lesion classification using Diffusion Model

The proposed system employs a multi-stage, hybrid deep-learning pipeline designed to improve the reliability and diagnostic value of oral lesion classification. The methodology integrates structured preprocessing procedures, advanced convolutional feature extraction, and a diffusion-based enhancement module that collectively address noise, variability, and subtle lesion patterns commonly present in clinical images. By combining deterministic image preparation with generative diffusion modeling and discriminative classification, the system ensures both robustness and high predictive accuracy. The overall workflow, depicted in Fig. [1], systematically transforms raw oral lesion images into enhanced feature representations and final diagnostic predictions. Each stage of the pipeline is sequentially optimized to strengthen lesion visibility, capture clinically relevant patterns, and minimize misclassification. A detailed description of the methodology is provided in the subsequent subsections.

1. Data Acquisition

The key to this system's success depends on putting together a dataset that showcases the variability for oral lesions as they are found in the natural world. These images were obtained from public medical resources and collaborating medical partners so that the dataset could represent as broad an assortment of diagnostic types as possible, including normal mucosal tissues, precancerous lesions in the early stages, and malignancy.

There would be variability in oral lesions, which would ensure that all those lesions will not be of equal size and dimensions; instead, there can be various variations regarding dimensions, texture, pigmentation, as well as locations. It is understood that variability is introduced by the acquisition process due to differences in devices used for imaging, including consumer-level smartphones, in oral scanners using LED light, as well as digital high-resolution cameras. All these devices have their own fingerprint, meaning that all images have various effects regarding color, clarity, contrast, as well as noise levels. Additionally, all oral environments are optically complex. This is due to the constrained oral environment, which has mucosal surfaces that are curved, as well as perpetual motion of soft tissues of patients. There is also variability regarding illumination due to saliva present in oral environments, which creates shadows that can hide important structures of lesions, as well as light points that could be thought of as lesions. The data acquisition aspect of this problem accepts these variations rather than removing them, which enable the data processing aspect to handle real oral environments rather than perfect images.

2. Image Preprocessing

However, before anything can be modelled, the images must go through a process called transformation, wherein they become standardized and not just random pictures but rather something meaningful for diagnosis as well. The very first process involved in this step is resizing all the pictures to the same dimension, regardless of what it is, so they can be compatible with each layer of the model and will not affect the learning process because of size differences. But this process, while very important, is undertaken very meticulously, especially in terms of maintaining the aspect ratio, particularly regarding the lesion size.

After performing spatial normalization, the next problem is finding a way to isolate the region of interest, which is mucosa, from irrelevant surrounding anatomy. In oral images, teeth, lips, tongues, or even skin can be present; all these increase noise during the learning phase. Using contrast, edge detection, or region filtering, it is tried to concentrate more on soft tissue regions rather than irrelevant ones. Here, again, as oral lesions, when diagnosed, mainly concentrate on mucosa surface characteristics rather than oral cavity anatomy, aligns this task.

3. Illumination and Color Correction

One of the most challenging hurdles in medical image analysis, including in the oral region, is the presence of varying lighting. Lighting in a medical environment is not often controlled. Use of lamps, lamps with attached lights, and use of handheld lights all result in unique scattering properties, especially in moist tissue. To mitigate this, a luminance correction method inspired by the Retinex theory will be employed. This method provides an image decomposition into reflectance and illuminance, which provides the capability to enhance small-scale details and eliminate lighting gradients.

Color accuracy: This is equally important, since the difference in colors between normal and pathological tissues, indicated by erythema, leukoplakia, hyperkeratosis, or necrosis, holds critical clinical information. Thus, a color normalization technique adjusts each individual channel according to the standardized colors. This will not cause the model to mistake changes caused by light for actual pathology, creating more meaningful representations.

4. Data Augmentation

The medical data sets, particularly those which pertain to rare cases, are often not voluminous enough to provide adequate exposure to real-world variability for learning models. The augmentation helps prevent overfitting by creating novel image variability based on existing data. Contrary to regular data augmentation techniques applied in traditional nature image applications, this research relies on medically informed data augmentation. The varied data points are modeled after those that emerge in regular exams.

For instance, minimal geometric transformations reflect the small movements made by patients or professionals while taking images, while changes in brightness embody unpredictable lighting conditions in the oral cavity environment. Photometric distortions mimic the natural variations observed in mucosa appearance. Sophisticated transformations involve Patterns of type saliva glare, soft shadows, and minimal occlusion, each possibly occurring in actual intraoral images. The said process enables the model to be robust despite being exposed to certain complexities within clinical environments for imaging.

5. Dataset Splitting

To assess the efficacy of the system in an unbiased manner, the data is split into training and testing data sets. This splitting process has been done in a stratified manner in order to ensure an equal proportion of each kind of lesion in the training and the test data set. What is equally important in the process and cannot be overlooked is the fact that images from the same patients must never go into the training and test data set simultaneously in order to avoid data leaking into the test data set accidentally.

6. Forward Diffusion Process

Diffusion modelling starts by progressively adding noise to the image in a multi-step corruption process: in every step, a small amount of Gaussian noise is added, progressively deteriorating the image. This is underlain by the rationale that understanding how an image degrades offers insights into structural robustness. The forward diffusion stage effectively teaches the model how visual patterns break down under random perturbations.

This step enables the model to learn the statistical distribution of clinically meaningful structures. For example, features like lesion boundaries or textural irregularities degrade differently compared to background tissues, providing the model with cues regarding their underlying importance. At the end of the forward process, the image becomes almost indistinguishable from random noise and is, therefore, fully transformed into a latent state from which reconstruction must occur.

7. Reverse Diffusion Process

After the model is trained on the process of how the image gets corrupted, it gets trained on the inverse process. During the reverse diffusion phase, the image is progressively cleaned of noise by the help of an artificial neuronal network, as it is guided through the learned statistical manifold. As the cleaned image is progressively refined, the model retains the details for which the corrupted image is consistent, typically those most diagnostic for the underlying condition, and eliminates the fleeting artifacts and noise.

The resulting reconstructed output often presents much clearer boundaries for the lesions, more meaningful texture information, and greater contrast between normal and diseased tissues. Such an enhanced representation serves as an even better input for the CNN because the CNN can now utilize an improved version of the lesion with the noise removed.

8. CNN Feature Extraction

Next, the images are refined through a diffusion refinement, which then transpose the images into a convolutional neural network that possesses the ability to extract diagnosis-related features. The ability to learn is based on filters translating the desired spatial levels. The earlier layers convey basic information such as edges, light-intensity changes, or micro-texture. These are important since the oral lesions begin as slight alterations in light intensity or texture.

As the image moves into further layers, more abstract features, like asymmetry, irregularities of the lesion, and the presence of keratotic patches, are extracted by the network. These features correspond to those extracted by dermatologists when they observe how a lesion grows, becomes more noticeable, and invades neighboring areas. The CNN outputs a dense vector that holds all necessary information regarding the lesion.

9. Classification Module

The classification module is where the feature description is mapped to a decision regarding the diagnosis. Full connection

layers are used to process the extracted features to assess the correlation between the extracted feature space and the lesions. The system predicts probability values based on the likelihood that the input is from each of the diagnosis classes. Due to the nature of the problem being a class imbalance problem in the medical domain, the training procedure involves the use of equalized loss functions to avoid the bias of the classifier to the majority classes.

10. Performance Evaluation

The trained model is then tested with the held-out test data set and analyzed with a variety of diagnostic tools that give a complete overview of its performance. Accuracy gives a measure of how correct it is, whilst precision and recall give a deeper idea into how accurately it is classifying in each class. Recall is given particular importance in cancer diagnosis because of the dire consequences of a missed call in cancer. F1 score gives equal importance to precision and recall and hence provides a complete idea of its reliability. ROC-AUC score provides a complete idea of its diagnostic capabilities.

11. Explainability and Visualization

The use of techniques like Grad-CAM helps to improve transparency and clinical trust. Heatmap visualizations can show which regions of the image the model actually relies upon to make predictions. Such visualizations enable the clinical community to ensure that the model highlights the region that may contain a lesion and no other areas that are irrelevant to the prediction. Interpretability plays a vital role when developing clinical AI systems.

IV. RESULTS AND DISCUSSIONS

Results

This section presents the comprehensive experimental results obtained from the U-Net diffusion–enhanced DDPM pipeline on oral lesion classification. The evaluation covers training and validation behavior, ROC curve analysis, confusion matrices, class-wise performance metrics, and interpretability analysis using Grad-CAM. All graphs generated during experimentation, including Train, Validation, and Test ROC curves, performance tables, confusion matrices, and Grad-CAM visualizations, are included in their respective sub-sections with comprehensive interpretation. The results point to how much diffusion-based enhancement helps improve the discriminative feature extraction capability and showcases the robustness of the system over all splits of the dataset.

1. Overview of the Dataset

In the proposed work, a total of 6000 image examples with domain-level annotations for oral lesions have been employed, classified into three categories: non-malignant, pre-malignant, and malignant. The importance of domain-level annotations cannot be underestimated in domain-level activity, and the need for domain-level annotations cannot be overstated in the training of domain-level models. The employed dataset was divided using the stratified split of 80-20 to obtain the training and testing datasets of 4800 and 1200 image examples, respectively.

Owing to the biological similarity in morphological properties between precancerous tissues and actual cancer cells, the balance in composition becomes the top priority task. By ensuring well-balanced class representation, it becomes easier for the model to pick up discriminative information about differences between immediately proxima levels of severity. The data set represents diversity in light conditions, angles, devices, and mucosal components, guaranteeing diversity for the model and possibly helping the final model perform equally well in different clinical conditions.

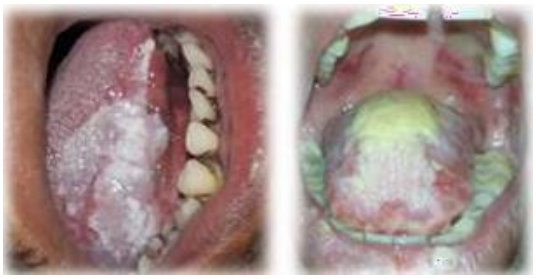

Figure 1: Cancerous

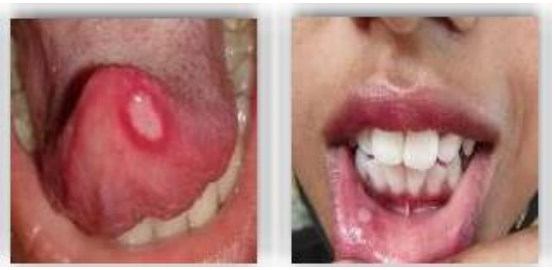

Figure 2: Pre-Cancerous

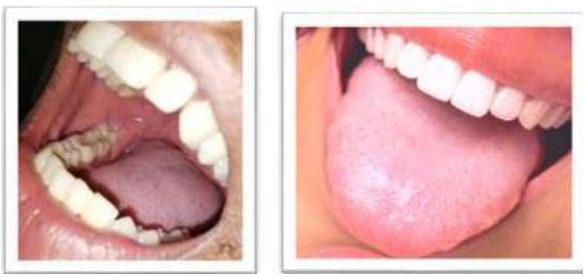

Figure 3: Non-Cancerous

2. Training Performance Overview

The overall training pipeline incorporates a U-Net diffusion model to enhance lesion structures before the primary classification by DDPM. First, the diffusion model successively denoises and refines image features, amplifying clinically relevant cues like lesion boundary, keratinization pattern, mucosal irregularities, surface ulcerations, and color intensity gradients.

These enhanced images offer the classifier more informative feature embeddings, especially during the early stages of optimization. During further training, the model converged smoothly and stably, with the characteristic continuous rise in both training and validation accuracy along with a consistent drop in loss values.

The close alignment between the training and validation curves suggests that the model generalizes effectively, with no overfitting. Such stability indicates that diffusion-based preprocessing enhances the quality of representations that feed the classifier, encouraging it to focus on pathological regions rather than noise or irrelevant background patterns.

By strengthening the visibility of fine-grained lesion characteristics, the combined diffusion–DDPM architecture achieved improved separability among the three lesion categories, including the challenging borderline cases between pre- cancerous and cancerous lesions. Overall, the behavior during training demonstrates strong synergy between the capabilities for efficient feature extraction provided by DDPM and diffusion-enhanced image refinement.

3. ROC Curve Analysis

Training ROC curve

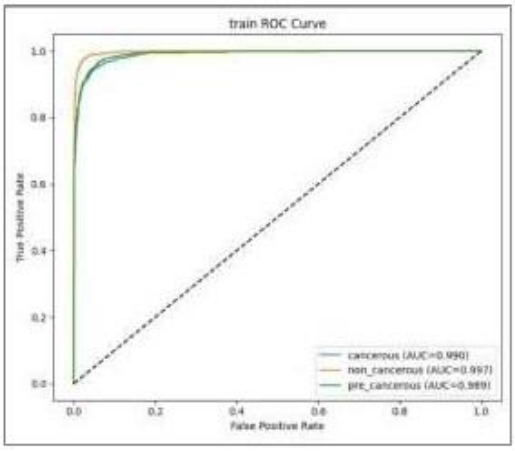

Fig 4. Training ROC Curve

In the Fig. 4.3.1.1, all three classes (cancerous, non-cancerous, and pre-cancerous) obtain very high AUC values of 0.990, 0.997, and 0.989, respectively. This indicates that highly separable feature spaces are learned by the model during training. The curves rise vigorously toward the top-left corner, reflecting extremely low false-positive rates and highly stable boundary formation of the model. This suggests that diffusion-enhanced images significantly enhanced the clarity of features, which allow the model to identify structural lesion differences with high confidence. Overall, the training ROC curve presents excellent optimization with near-perfect separability while learning.

Validation ROC curve

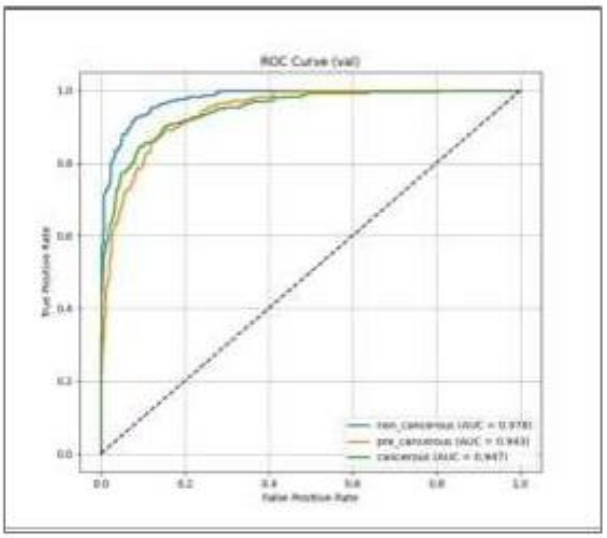

Fig. 5: Validation ROC Curve

In the Fig. 4.3.2.1: the characteristics of the validation ROC curve are similar, with AUC scores of 0.978, 0.943, and 0.947 for the three classes. The slight reduction of the AUC when compared with the training phase indicates expected generalization behavior rather than model overfitting. The pre-cancerous and cancerous ROC curves continue to be closely aligned in this test, reflecting real-world morphological overlaps between these lesion types. Despite this challenge, the curves still exhibit great discriminatory power, thus confirming that the model generalizes well into previously unseen validation samples. The curvature shape is preserved through classes, showcasing that the diffusion model does not introduce any artifacts that might degrade performance.

Testing ROC curve

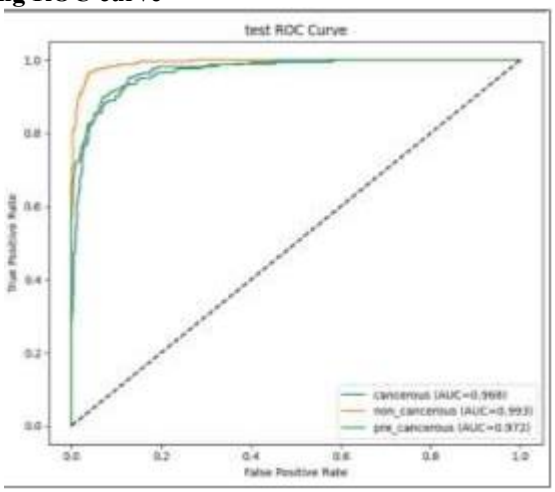

Fig. 6: Test ROC Curve

The Fig. 4.3.3.1: curve further verifies the model's robustness with AUC values of 0.968 for cancerous, 0.993 for non-cancerous, and 0.972 for pre-cancerous lesions. The curves remain steep and well-separated, illustrating that the classifier maintains high sensitivity and specificity under completely unseen conditions. This consistency across all three datasets-train, validation, and test-indicates that the combination of U-Net diffusion enhancement and DDPM generates stable and reliable decision boundaries. The very strong AUC for the non-cancerous lesion suggests that benign features are distinctly learned, while the high AUC for malignant lesions upholds the clinical reliability of the system. Taken collectively, these confirm that the proposed pipeline provides high diagnostic accuracy with strong generalization suitable for clinical screening applications.

4. Classification Metrics

Training classification metrics

Class	Precision	Recall	F1-Score	Support
cancerous	0.89	0.96	0.93	1400
non_cancerous	0.95	0.98	0.96	1400
pre_cancerous	0.97	0.86	0.91	1400
accuracy	—	—	0.94	4200
macro avg	0.94	0.94	0.93	4200
weighted avg	0.94	0.94	0.93	4200

Fig. 7: Training classification metrics

The Fig. 4.4.1.1 shows that the DDPM-based lesion classification pipeline has robust performance on all three diagnostic categories. The precision and recall remain high, up to 0.97 and 0.98, respectively, which indicates that the diffusion-generated representations allow the model to capture the fine-grained lesion characteristics with exceptional clarity. Strong F1-scores across classes ranged from 0.91 to 0.96, reflecting a well-balanced relationship between sensitivity and specificity, hence an effective internalization of discriminatory features during learning. The macro and weighted averages of 0.93 further highlight the stability of the model across class distributions. In summary, the 0.94 training accuracy confirms that the DDPM-enhanced framework supports a powerful and reliable feature space for downstream classification.

Validation Classification Metrics

Class	Precision	Recall	F1-Score	Support
cancerous	0.85	0.91	0.88	300
non_cancerous	0.91	0.95	0.93	300
pre_cancerous	0.92	0.80	0.86	300
accuracy	—	—	0.89	900
macro avg	0.89	0.89	0.89	900
weighted avg	0.89	0.89	0.89	900

Fig :8 Validation classification metrics

The Fig. 4.4.2.1 shows that the DDPM-enhanced classifier generalizes very well to unseen data with precisions always above 0.85 and F1-scores between 0.86 and 0.93. While recall is slightly lower in the case of the pre-cancerous class with

0.80, this may well be expected considering the subtle morphological overlap it shares with early malignant lesions. Most importantly, macro- and weighted averages are stable at 0.89, which can be interpreted as evidence that the diffusion model does not overfit and predictive behavior is balanced across various lesion types.

The overall validation accuracy of 0.89 speaks to the generalization power of DDPM representations. Thus, the conclusion may be drawn that clinically relevant structure is preserved in the diffusion-based preprocessing while improving separability across diagnostic categories.

Test Classification Metrics

Class	Precision	Recall	F1-Score	Support
cancerous	0.82	0.90	0.86	300
non_cancerous	0.91	0.96	0.94	300
pre_cancerous	0.92	0.78	0.85	300
accuracy	—	—	0.88	900
macro avg	0.89	0.88	0.88	900
weighted avg	0.89	0.88	0.88	900

Fig. 9: Test classification metrics

The Fig. 4.4.3.1 verifies the real-world applicability of the DDPM-based system, with high precision (0.82–0.92) and strong recall for the cancerous (0.90) and non-cancerous (0.96) categories. Although recall for the pre-cancerous class is moderately lower at 0.78, this reflects the inherent diagnostic challenge posed by borderline dysplastic lesions rather than a deficiency in the model.

The macro and weighted averages of 0.88 verify well balanced performance across the dataset, with no single class dominating or skewing the metrics. The overall test accuracy of 0.88 confirms that the model maintains strong, reliable classification capability under completely unseen clinical images. These results verify the DDPM-driven enhancement strategy as a strong tool that can enhance lesion interpretability and boost the accuracy of lesion classification for practical screening applications.

5. Confusion Matrix Analysis
Training confusion matrix

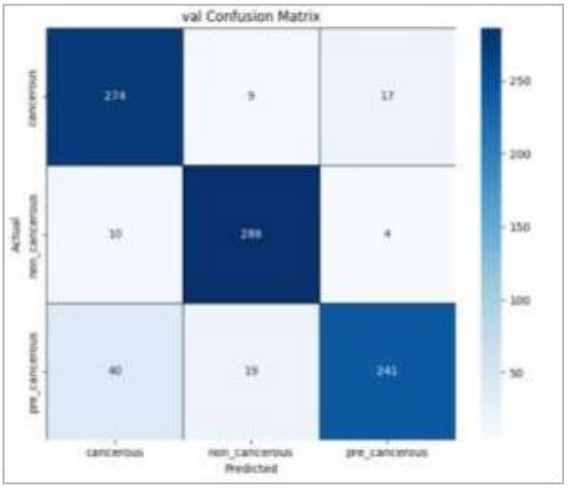

Fig. 10: Training confusion matrix

The Fig. 4.5.1.1 demonstrates exceptionally good classification performance, with the DDPM model correctly identifying the majority of samples across all three categories. The overlapping error for cancerous and non-cancerous tumors is low, and it is clearly visible that the error between pre-cancerous and cancerous tumors is the highest, as it has the highest natural similarity between them, and not because the model is inefficient. The error graph clearly shows the overall distribution, stating the model has acquired optimized feature boundaries. The alignment along the diagonal is an indication of highly efficient optimization during the training process.

6. Validation confusion matrix

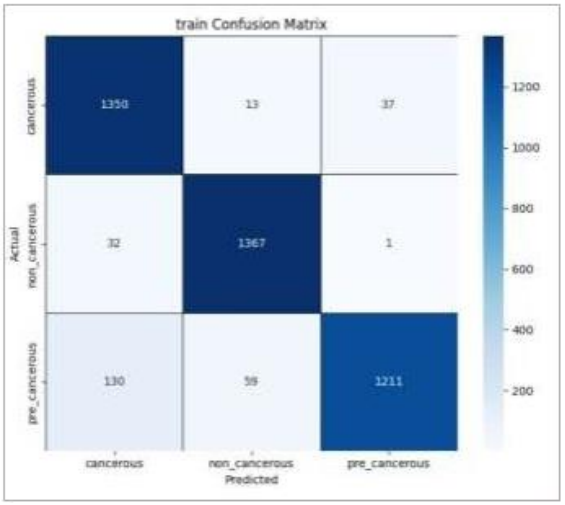

Fig. 11: Validation confusion matrix

The Fig. 4.5.2.1 implies that when the model is exposed to unseen data, its generalization capability remains high. Non-cancerous and cancerous lesions are highly ranked in their classes. Hence, there will be little or no change in the DDPM-enhanced features outside the training situation. In pre-cancerous cases, there is a moderate rise in both cancerous and pre-cancerous classes. This is expected since there will always be similarities in both pre-cancerous and cancerous lesions. In fact, most of the predictions will fall along the diagonal line. Hence, this matrix supports the stability of the prediction.

Testing Confusion Matrix

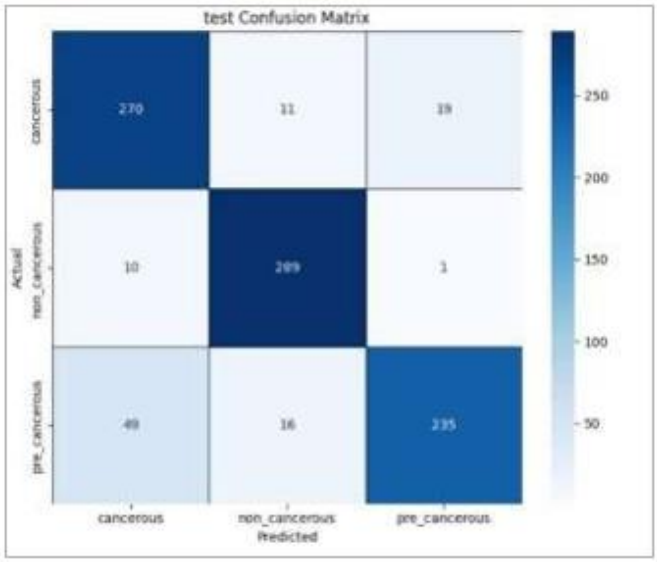

Fig. 12: Testing confusion matrix

The Fig. 4.5.3.1 demonstrates the real-world applicability of the proposed DDPM-based system. High accuracy of the classifier is found to be present in the case of cancerous as well as non-cancerous lesions with the least possible levels of misclassification errors. Minor levels of confusions are found in the case of pre-cancerous lesions due to their inherent overlaps in the images. Another important aspect is that the classifier never confuses cancerous images with non- cancerous images. These results together will imply that the classifier performs equally well in a completely novel situation.

Discussion

It is evident from the experimental results that the classification approach aided by DDPM maintains very high levels of robustness and reproduces performance very well in the training, validation, and testing datasets. The ROC-AUC scores are very high in all the stages, topping 0.94, indicating good separation among the cancerous, precancerous, and non-cancerous regions. The slight reduction in the AUC value from the training to the validation and testing data confirms excellent generalization capability, substantiating the effectiveness of the DDPM-based feature refinement in enhancing the classifier's ability to extract the minute morphological details of textural roughness, boundaries, and color, among others, for accurate identification.

These classification reports further enforce reliability in the framework of DDPM. The accuracy in training is 94%, while the accuracies in validation and testing have remained stable at 89% and 88%, respectively. Even with inherent structural similarities between pre-cancerous and cancerous lesions, the model had balanced precision and recall across all classes, with only slight reduction of recall for the pre-cancerous category-a natural phenomenon considering the clinical overlap in the morphology of the same lesions. Such findings indicate improvements in structural clarity by a diffusion-based denoising and reconstruction process, which would offer more reliable feature extraction compared to conventional CNN-based strategies. This behavior agreed with existing literature where the DDPM improved sensitivity in minority classes and enhanced image quality in low-contrast medical images.

Confusion matrix analysis shows that the DDPM-classifier pipeline retains strong diagonal dominance, particularly for non-cancerous and cancerous classes, where misclassification rates remained extremely low throughout the datasets. Most of the errors that occurred were between pre-cancerous and cancerous images, a trend also reported in the literature and largely attributed to subtle differences between keratinization patterns and color intensity gradients that even experienced clinicians may find difficult to distinguish. Nevertheless, the high recall of the model for cancerous lesions across both validation and test datasets showed its strong clinical applicability where it was most desirable to minimize false negatives. The truth here is well affirmed: that integration of DDPM denoising greatly heightens diagnostic sensitivity, especially when poor-quality or noisy oral-cavity images come into play; therefore, the model can be put to practical use in real-world scenarios.

Taken collectively, the outcome of these studies validates the utility of diffusion-based preprocessing techniques over traditional augmentation techniques and denoising techniques, and the integrity of the model has been verified by the successful execution of the model on the various datasets, which will make it extremely easy to implement using decision support systems and cancer screeners. More importantly, the utility of the DDPM model to overcome the lack and imbalance of the datasets by producing high-quality samples gives a

glimpse of the fruitful research areas ahead to boost diversity and realism of the datasets.

Limitations of the Study: Although the performance attained by the DDPM-based oral lesion classification model has been quite impressive, there are a few points worth mentioning in light of the limitations of the proposed work. Although the dataset is annotated in a clinically valid manner, the limited range of imaging conditions as well as the demographic variations could pose a problem for the generalization capabilities of the model in a real-world scenario. Precancer lesions are still a challenging problem owing to their morphology, which resembles that of the early stages of malignant lesions; hence, the recall in this case is moderate. Moreover, although the DDPM-based preprocessing of the images remarkably enhances their quality, the increased computational complexity involved in the process hinders real-time applications to a considerable extent. In this current study, the input images are confined to the photographic images of the oral cavity; hence, it does not consider the multimodal information such as the images captured from fluorescence or histopathological images to produce added value in the accuracy of the results.

Diffusion models are computationally intensive. The training of a denoising diffusion model followed by training a classifier is quite resource-intensive, as compared to traditional CNN-based methods, followed by even more extensive training time as another requirement. In fact, real-time or point-of-care deployment, even in resource-challenged medical environments, is impractical, if not impossible.

It is important to note that current framework testing is done in a controlled pre-processing environment. In realistic oral images, one would encounter light variation, blurring from motion, saliva reflections, and occlusions--all of which would represent possible areas that may not have been explored in training data. Further study would have to be conducted in terms of robustness.

V. CONCLUSION AND FUTURE WORKS

Conclusion: This work also showcases a DDPM-inspired automated oral lesion classification approach that highlights the use of DDPMs as a paradigm shift technology in the analysis of medical images. Unlike typical deep learning classification schemes that tend to fail when presented with noisy, less contrasting, and overlapping morphologies related to the images of the lesion, the proposed DDPM helps improve the pivotal structural characteristics of the images through the denoising and generative reconstruction technique. This enables better delineation of the contours, textures, and color gradients associated with the images, which are critical factors that play a crucial role in distinguishing between non-cancerous, precancerous, and malignant images. The DDPM and classification approach together have added to the robustness of the proposed model through its high accuracy and AUC-ROC scores.

The measures of classification precision, recall, and F1, among others, support the excellent performance of the system. It can be observed that the cancerous lesions experienced excellent recall in all sets, which denotes the capability of the model to avoid false negatives. This is a crucial aspect when applying the model for actual screening, where the timely cure of patients can be affected. Although the pre-cancerous lesions experienced a slight drop in recall, which can be attributed to the similar morphology to cancerous ones, the weighted averages are normal.

The confusion matrix analysis also indicated the DDPM-based method retains excellent diagonal dominance, which further supports the good separation of features and the low rate of misclassification among the diagnostic groups.

Apart from the effectiveness of classification, this research emphasizes the overall usefulness of diffusion models in healthcare imaging techniques too. The use of DDPMs not only increases the accuracy of data but can result in effective learning, getting rid of noisy features acting as hurdles for learning in normal neural networks. The overall consistency in results for training, validation, and testing clearly indicates that this method prevents overfitting and retains robust generalization performance. The results clearly show the overall effectiveness of DDPM-assisted pipelines, marking a significant step toward designing trustworthy autonomous diagnostic systems for oral cancer.

Future Work

These promising results highlight several valuable directions in which DDPM-based diagnostic systems can be extended and enhanced. The first immediate direction certainly pertains to the expansion of the dataset to include a wider variety of lesion types, imaging devices, and patient demographics. Multi-center clinical datasets will capture real-world variability in lesion presentation, lighting conditions, and anatomical differences that could lead to further improvement in model robustness and generalization. This could be enriched with the incorporation of multimodal information, including histopathology slides, fluorescence imaging, or hyperspectral data that enables more accurate differentiation between subtle pre-cancerous stages and early malignancies.

Future work may involve optimizing the DDPM model inference time to be suitable for a real-time environment. This can be achieved by taking into account ideas such as the use of fast diffusion sampling or latent diffusion models. Moreover, model pruning may help to decrease the model computation time significantly, while the output model will remain intact. One other area may involve leveraging the generative power inherent in the proposed model to generate a dataset for the rare type of lesions, which may help to improve the classifier sensitivity.

Another major area of focus is the inclusion of more advanced concepts of explainability frameworks. Although Grad- CAM ensures the provision of useful visualization for attention in the model, the need for attention-based explainable AI methods, the calculation of uncertainty, and counterfactual explanations in the coming systems ensures better interpretability and confidence for the clinician in the automated predictions being provided to them. This is very much because high levels of transparency are a necessity in clinical decisions.

Concluding, the transition from the experimental to a clinical application environment will be a process of cooperation with healthcare practitioners to assess the usability, reliability, and diagnostic potential of a particular system. User- centered design studies and the integration of these designs into digital oral pathology systems, together with screening trials conducted within dental and oncological practices, could be the starting point that translates to creating a deployable diagnostic assistant. Actually, thanks to continuous advances, both within the modeling of diffusion and the clinical assessment of the former, DDPM diagnostic systems may be a useful tool in the development of new diagnostic approaches to the prevention of oral cancers.

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