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Novel multilevel local binary texture descriptor for oral cancer detection

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ABSTRACT

Categorizing texture medical images is an extensive job in most of the fields of computer vision, pattern recognition and biomedical imaging. For the past few years, the texture analysis system model, especially for biological images, has been brought to attention because of its ever-growing requirements and characteristics. This research shows its novelty by using a multilevel local binary texture descriptor (MLBTD) algorithm with support vector machine (SVM), k-nearest neighbor (KNN), and CT Classifiers to investigate the texture features of the oral cancer samples. The simulation work is done in $MATLAB_{2021a}$ environment by employing the MLBTD algorithm. A Mendeley dataset, containing 89 oral cavity histopathological images and 439 OSCC images in 100x magnification, is used. A statistical comparative study of local binary pattern (LBP) and MLBTD with linear SVM, KNN, CT classifier is performed in which results show the better performance of MLBTD and linear SVM with 89.94% of accuracy and by applying MLBTD algorithm over 90.57% accuracy is obtained whereas LBP algorithm only provides 86.16% of accuracy.

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1. INTRODUCTION

Oral cancer is one of the diseases that is known to spread rapidly all over the globe. There are roughly 177,757 fatalities that are predicted to be caused by oral cancer, and there are 354,864 new cases per year [1]. However, due to a lack of information about the signs of mouth cancer, the majority of cases are discovered in the later stages of the disease. The survival rate for oral cancer may range from 75 to 90 percent if it is recognized in its early stages. The improvement of vision-based adjunctive techniques that can differentiate between oral and potentially malignant illnesses is one of the most effective strategies for medical professionals to identify mouth cancer. Surgery is the most fundamental kind of medical therapy because it guarantees a high likelihood of success and offers a survival rate between 75 and 90 percent in the early phase [2]. Despite this, sixty-five to sixty-five percent of cases are discovered in the late stage, with a considerable ratio of fatalities [3]. In the context of any wellness program that seeks to understand the mortality ratios and the severity of the condition, the diagnosis of oral cancer becomes very important. Oral squamous cell carcinoma, also known as OSCC, is responsible for more than ninety percent of all occurrences of oral cancer, including leukoplakia and erythroplakia, which are preceded by oral potentially malignant diseases (OPMD). The diagnosis of OPMD is associated with a high probability of fatal conversion, as well as a reduction in the fatality ratio of oral cancer and the need to pay attention to screening programs. Due to the fact that these screening programs are only dependent on ocular analysis and are carried out by primary care health practitioners, who are often not capable of identifying oral cancer tumors [4], [5], it is uncertain whether or not they will be effective in their implementation. There is a great amount of variation in the symptoms that are associated with oral cancer malignancies, which makes it very difficult for medical professionals to make a diagnosis. As a result, this variation is considered one of the primary reasons patients' referrals to oral cancer specialists are delayed [5]. On the other hand, initial-stage oesophageal squamous cell carcinoma and oesophageal squamous cell carcinoma malignancies are often asymptomatic and manifest as benign, non-toxic malignancies, typically delaying subsequent identification. The development of contemporary computer vision methods and machine learning techniques has resulted in strong models that can perform automated screening of oral lesions and provide medical experts with the most effective therapy for these lesions.

Machine learning models are presented to precisely compare highly distinguished OSCCs and somewhat differentiated OSCCs [6]. Machine learning models may predict the first phase of lymph node metastasis caused by oral tongue squamous cell carcinoma [7], and these models also contribute to determining the illness's outcomes [8]. Using machine learning models greatly assists the investigation of various cancerous tumors. The dissemination of ML apps solely depends on clinical documentation of illness and the interpretation and prevention of potentially malignant oral contusions [9]. The automated detection of oral malignancies, benign contusion, and oral potentially malignant disorders (OPMDs) broadly depends on the microscopic representation of the images [10]-[13]. Some other studies include the implementation of multi-dimensional hyperspectral images of the cavity [14], the application of computed tomography (CT) images [15], the application of autofluorescence [16], [17] and fluorescence imaging [18], which emphasizes on the comparative view of oral malignancies and white light images for oral cavity texture [19]-[21].

In the beginning of this area, mainly characteristics related to texture have been directed. The gray level co-occurrence matrix and grey level run-length are operated by Thomas et al. [19], LPB (Local Binary Pattern), laws texture energy, and higher order spectra are utilized by Krishnan *et al*. [10]. The recent studies [11]-[18], [20], [21] gave a boom to deep learning, i.e., artificial neural networks (ANN), which resides in multiple layers of neurons and requires huge datasets. These recent techniques offer fast computing speed, which helps investigators investigate and solve critical problems. Advancements in this field have provided an efficient application of deep convolutional neural network (DCNN). After conquering the ImageNet [22] image classification contest in the year 2012 along with AlexNet [23], the convolutional neural networks became famous in the computer vision domain.

In the early stages, convolutional neural networks (CNNs) are operated on image characterization (Classification of image in a specified domain). CNN-based framework designing has been announced as a significant breakthrough in the object detection field, like PASCAL visual object classes [24] and common objects in context (COCO) [25]. The maximum accuracy is achieved by the R-CNN group (region-based CNN technique) [26], Fast R-CNN [27], Faster R-CNN [28], and the recent Mask R-CNN [29]. Single-level detectors like you only look once (YOLO) [30] and single shot detector (SSD) [31] are the faster techniques to achieve good accuracy. In the medical imaging field, object detection frameworks have been employed along with Faster R-CNN for colon polyp detection [32] as well as the characterization of malignancies in mammograms [33]. Anantharaman *et al.* [21] have worked on oral cancer images using the Mask R-CNN technique using 40 40-image dataset. Their study was to diagnose benign oral cavities (herpeslabialis and aphthous ulcersusing instance segmentation. An authentic clinically tested dataset is required for the most accurate automatic diagnosis of early oral malignancy. By making use of deep learning algorithms, accuracy, and efficiency can be enhanced to the broadest possible data. In 2021, to access the four datasets: EBSCO, PubMed, OVID, and Scopus, the University of Sharjah Library was utilized to manage the investigation. The discoveries were released in the year 2000-2021 and have presented a robust improvement in the detection and treatment of oral cancer using AI, ML, DL, and neural networks. To find the research, a set of keywords like “machine learning” [MeSH term] OR “neural network” [MeSH term]) were utilized to find the articles in all four databases for the appropriate screening of articles. These Dental Journals can be found using the manual search options, which are: Journal of Oncology, Journal of Oral Diseases, Journal of Oral Pathology and Medicine and Oral Surgery Oral Medicine, Oral Pathology Oral Radiology, International Journal of Oral and Maxillofacial Surgery, European Journal of Craniomaxillofacial Surgery, British Journal of Oral and Maxillofacial Surgery, and Journal of Craniofacial Surgery. With the help of the following research reference lists, many studies can be managed. Additionally, He *et al*. [34] presented deep residual learning for image recognition. In which Faster R-CNN is adopted as a detection method. Yaduvanshi *et al*. [35] is discussed an automatic classification methods in oral cancer detection. Previous research has shown noteworthy improvement in cancer detection; however, the performance of the systems is challenging because of low feature distinctiveness and poor correlation between global and local characteristics of the cancer images.

Vijaya Yaduvanshi *et al*. [36] has given an automatic oral cancer detection and classification using modified local texture descriptor and machine learning algorithms in which convolutional neural network (CNN) is used for better texture feature representation. Traditional texture descriptor techniques are challenging due to scale variance, larger feature vectors, rotation invariance, and sensitivity to uneven illumination, noise, and blur. The outcomes of the ML classifier are hugely affected by the size and length of the features.

The research paper represents a multilevel local binary pattern technique to investigate the texture features in oral cancer images. This is a proven novel technique to differentiate texture oral cancer samples with significantly good accuracy. In the proposed work, a multilevel local binary pattern is used to investigate the texture features of the oral cancer samples. The results establish the advantages of the proposed algorithm in characterizing the texture of oral cancer images. also, it provides more precise features for texture in oral cancer Images. It is proved that the MLBTD algorithm gives better accuracy than the LBP algorithm, with 90.57% accuracy. Also, the overall performance of MLBTD with support vector machine (SVM) classifier outperforms in contrast with MLBTD with k-nearest neighbor (KNN) and MLBTD with classification tree (CT) algorithms.

In the present scenario, oral cancer characteristics, by its occurrence ratio, the requirement to boost its prevention methods, and many studies are prescribed for applying ML models. For these types of malignancies, extensive research was carried out to establish an efficient application of ML algorithms in detecting oral cancer. [9]

The paper's arrangement is as follows: Section 2 represents the background and theory of the proposed work. Section 3 represents the proposed design and operating principle. Section 4 shows the results and discusses the proposed algorithm. Section 5 describes the conclusion and future scope of the work.

2. METHOD

A machine learning-based approach using collaborative texture and color features is proposed. The proposed multilevel local binary texture descriptor (MLBTD) considers more than one label for the binary value computation to improve the texture information of the oral cavity images (Figure 1). Figure 2 represents the MLBTD algorithm, which illustrates the connection of the pixel to their local neighborhood with texture feature representation in the existing and proposed methodology. In the pre-processing stage, the RGB picture sample is reformed to a grayscale picture.

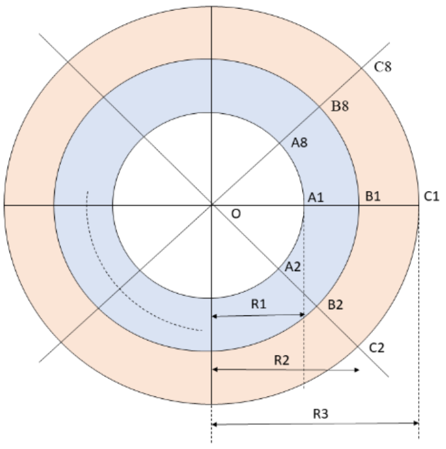

Figure 1. Multilevel local binary pattern (MLBTD)

MLBTD algorithm is proposed to offer an adequate texture descriptor. LBP histogram is generated for different block sizes (N). Support vector machine, k-nearest neighbor, and classification Tree classifiers are used. Accuracy will suffer because of the class imbalance problem, so synthetic data is generated with the existing data. Generally, Gabor transform is used, but this research is done on texture and color features. The textural structure of any image depends upon the more minor changes in the intensity, and cancerous cells in the oral cavity bring the non-homogeneity in the texture. The local binary pattern is computed using (1) and (2). The histogram of the MLBTD descriptor is computed to minimize the feature vector. It represents that higher importance is given to the immediate neighbor and lower importance is given to the farther neighbor.

It is a rotation invariant and scale variant. It shows better performance for uneven illumination changes and blurred conditions.

$$MLBTD(x) = \begin{cases} 1 \; if \; s(x) \geq 0 \\ 0 \; otherwise \end{cases} \tag{1}$$

$$s(x) = (A_1 - A_0) * R + (A_2 - A_0) * (R - 1) + (A_3 - A_0) * (R - 2) + \cdots \tag{2}$$

$$s(x) = \sum_{i=1}^{R} (A_i - A_0) * (R - i - 1) \tag{4}$$

Where, the window radius is R, center pixel in the window is Ao, and location of the neighboring pixel is i.

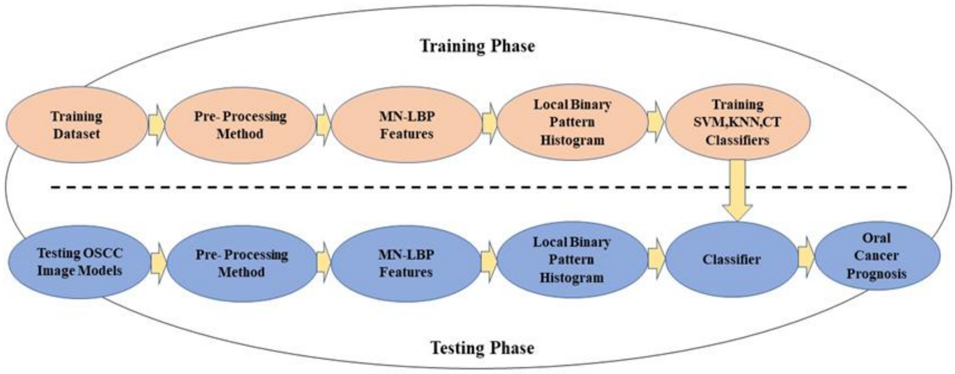

Figure 2. Flow diagram of the proposed algorithm.

3. RESULTS AND DISCUSSION

In the experimentation, 100x resolution benign histopathological image is taken from the publicly available Mendeley dataset, which consists of a Total of 1224 images [37]. Images are differentiated into two categories with two different resolutions. The first category consists of 89 histopathological images with the normal epithelium of the oral cavity and 439 images of oral squamous cell carcinoma (OSCC) with 100x magnification. The second category consists of 201 images with the normal epithelium of the oral cavity and 495 histopathological images of OSCC with 400x magnifications. The images were captured using a Leica ICC50 HD microscope from H&E stained tissue slides collected, designed, and cataloged by medical experts from 230 patients. Figure 3 represents the different versions of the sample image. Figure 3(a) shows original sample image, Figure 3(b) illustrates the gray converted image, Figure 3(c) represents MLBTD for R=1, Figure 3(d) displays MLBTD for R=2, Figure 3(e) depicts MLBTD for R=3, Figure 3(f) shows LBP descriptor for R=1, Figure 3(g) displays MLBTD histogram N=1 and Figure 3(h) visualizes MLBTD histogram for N=2. It can be observed that MLBTD descriptor shows good texture feature representation in contrast with the conventional LBP texture descriptor. MLBTD descriptor for various block size (N) and radius (R) are shown in Figure 3.

Results are shown using the OSCC dataset, which consists of 439 photos of OSCC at 100x magnification and 89 histological images showing the oral cavity's normal epithelium. Table 1 compares the MLBTD method and the local binary pattern (LBP) approach using a linear support vector machine (SVM) for block sizes N = 1, 2, 3, and 4. For N=3 with 2295 total no. of features, 86.16% accuracy, 0.57 recall, 0.78 precision and 0.66 F1-score is achieved in LBP+SVM and 90.57% accuracy, 0.68 recall, 0.85 precision and 0.75 F1-score is achieved in MLBTD+SVM, the LBP and MLBTD comparison is done with the k-nearest Neighbour (KNN) for Block size N=1,2,3,4. For N=3 with 2295 total no. of features, 82.25% accuracy, 0.46 recall, 0.70 precision and 0.56 F1-score is achieved in LBP+KNN and 88.68% accuracy, 0.63 recall, 0.81 Precision and 0.71 F1-score is achieved in MLBTD+KNN, the LBP and MLBTD algorithms with Block size N=1,2,3,4 and compared with the classification tree (CT). For N=3 with 2295 total no. of features, 82.84% accuracy, 0.48 recall, 0.70 Precision, and 0.57 F1-score is achieved in LBP+CT and 89.94% accuracy, 0.67 recall, 0.81 Precision, and 0.73 F1-score has achieved in MLBTD+CT The findings show that using an SVM classifier in conjunction with the MLBTD method improves accuracy and other measurement metrics. MLBTD texture descriptor provides a good texture representation of the histopathological images and improves the accuracy of the evaluation of malignant regions in OSCC images. Up to block size, N=4 contributes good results, but on further increasing block size, the accuracy would be affected because of the redundancy in the features.

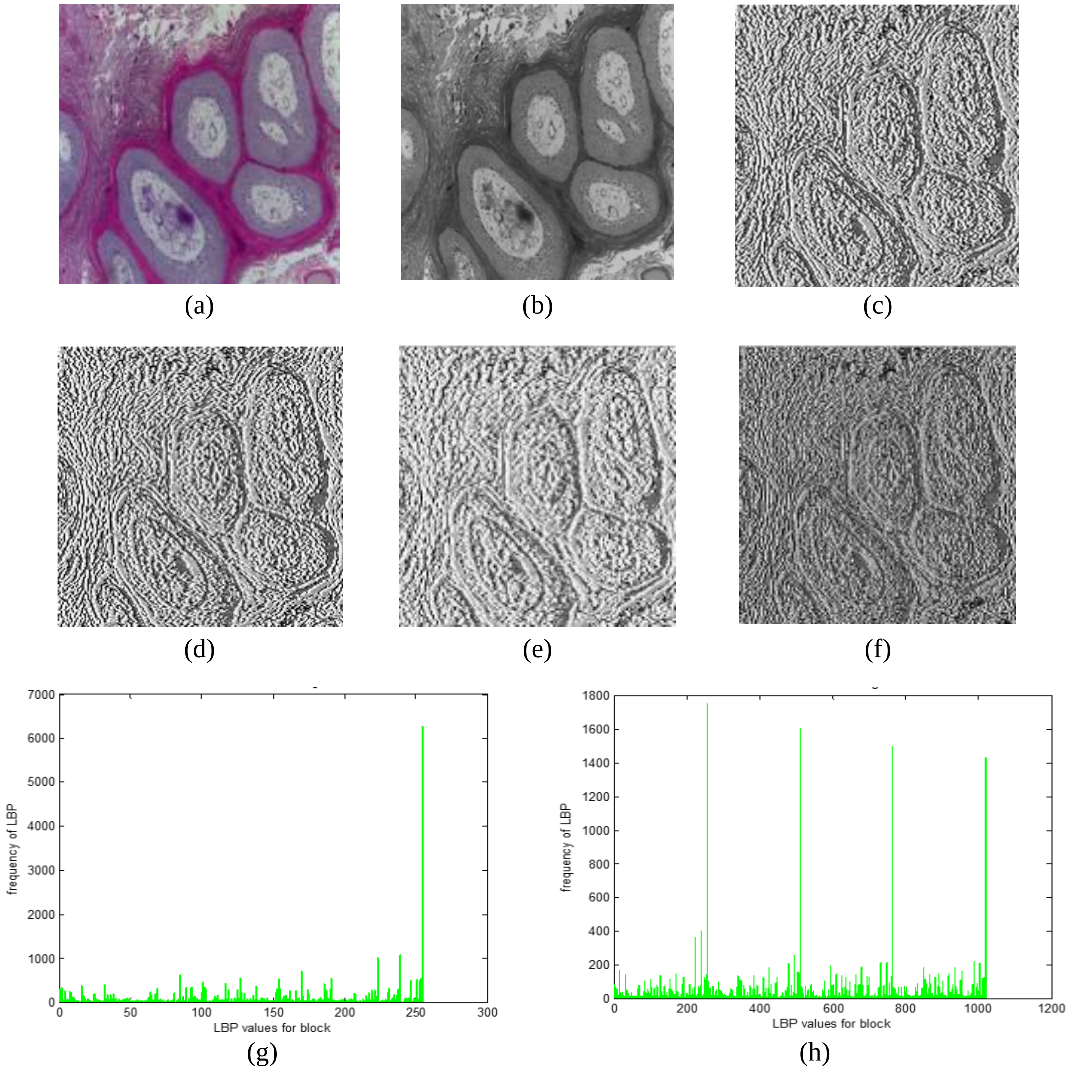

Figure 3. Visualization of the MLBTD results (a) colored image (b) greyscale image (c) MLBTD for R=1, (d) MLBTD for R=2, (e) MLBTD for R=3, (f) LBP for R=1, (g) MLBTD histogram N=1, (h) MLBTD histogram for N=2

The comparative results of the MLBTD are provided in Table 2 where results of MLBTD are compared with histogram of oriented gradient, grey level co-occurrence matrix (GLCM) and LBP. It is observed that the MLBTD offers superior results than HOG, LBO and GLCM. GLCM, a texture-based method, achieved relatively lower accuracy across all classifiers, with the highest being 68.30% using SVM. HOG, which focuses on object shape and edge information, performed better, with a maximum accuracy of 78.85% (SVM). LBP, capturing local texture patterns, showed significant improvement, reaching 86.16% with SVM. The most effective scheme, MLBTD, combining multiple texture descriptors, achieved the highest overall accuracy, with SVM reaching 90.57%, followed closely by CT (89.94%) and KNN (88.56%). This shows a clear trend of improving accuracy from basic texture methods (GLCM) to more advanced texture-describing techniques (MLBTD), with SVM consistently outperforming the other classifiers across all schemes.

The MLBTD offers a significant improvement in the local feature depiction than the convention LBP scheme by providing the multi-neighbor relationship between the adjacent features. The features shows the scale invariance and rotation invariance because of the histogram features which are independent on the scale and rotation of the images. The MLTBD histogram provides imperative reduction in the feature vector length which helps to achieve the lower recognition time (0.12 sec per sample). This study provided excellent results for the various ML classifiers however the performance of the system is limited for the larger datasets and multi-level cancer detection system. The system lacks in providing the interpretability and explainability for cancer detection.

Table 1. Performance metrics comparison of proposed MLBTD and LBP features with various ML classifiers by varying block size

Algorithm	No of Blocks	Number of Features	Accuracy	Recall	Precision	F1-score
LBP+ Linear SVM	N=1	255	83.02	0.50	0.74	0.60
	N=2	1020	84.28	0.53	0.74	0.62
	N=3	2295	86.16	0.57	0.78	0.66
	N=4	4080	85.53	0.56	0.74	0.63
MLBTD+ Linear SVM	N=1	255	88.05	0.61	0.81	0.70
	N=2	1020	89.31	0.65	0.81	0.72
	N=3	2295	90.57	0.68	0.85	0.75
	N=4	4080	89.94	0.67	0.81	0.73
LBP+KNN	N=1	255	76.73	0.38	0.59	0.46
	N=2	1020	79.25	0.43	0.67	0.52
	N=3	2295	82.25	0.46	0.70	0.56
	N=4	4080	79.87	0.44	0.67	0.53
MLBTD+KNN	N=1	255	85.53	0.56	0.74	0.63
	N=2	1020	87.42	0.60	0.78	0.68
	N=3	2295	88.68	0.63	0.81	0.71
	N=4	4080	86.79	0.58	0.78	0.67
LBP+CT	N=1	255	76.73	0.39	0.63	0.48
	N=2	1020	79.50	0.43	0.70	0.54
	N=3	2295	82.84	0.48	0.70	0.57
	N=4	4080	80.50	0.45	0.70	0.55
MLBTD+CT	N=1	255	86.16	0.57	0.78	0.66
	N=2	1020	88.05	0.61	0.81	0.70
	N=3	2295	89.94	0.67	0.81	0.73
	N=4	4080	87.42	0.59	0.81	0.69

Table 2: Comparative results of MLBTD with traditional methods [38]

Feature extraction Scheme % Accuracy	Classifier		
	KNN	CT	SVM
GLCM	63.45	66.50	68.30
HOG	72.40	74.80	78.85
LBP	82.25	82.84	86.16
MLBTD	88.56	89.94	90.57

4. CONCLUSION

This paper uses a multilevel local binary texture descriptor to identify oral cancer. The classifiers utilized for the classification include SVM, KNN, and CT. Different block sizes and radii are used to assess the performance of the local binary pattern (LBP) and MLBTD. 88.05% accuracy, 0.81 precision, 0.61 recall, and 0.70 f1-score are obtained using the MLBTD method with block size N=1 and 255 features. Results include 89.31% accuracy, 0.81 precision, 0.65 recall, and 0.72 f1-score for block size N=2 with 1020 features. It is possible to get 90.57% accuracy, 0.85 precision, 0.68 recall, and 0.75 f1-score with block size N=3 and 2295 features. Block size N=4 with 4080 features yields 89.94% accuracy, 0.81 precision, 0.67 recall, and 0.73 f1-score. Consequently, it is discovered that for an equivalent number of features, MLBTD outperforms LBP by observing the performance parameters: accuracy, precision, recall, and f1-score. Furthermore, compared to the KNN and CT classifiers, MLBTD with the SVM classifier performs better. Thus, in the future, the focus can be given to improving the feature representation using DL-based algorithms and enhancing the interpretability and explainability of the systems. The effectiveness of the classifiers can be boosted by combining the color and shape features with the texture features. In the future, deep learning algorithms can improve feature depiction and address class imbalance.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Vijaya Yaduvanshi	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			
Raman Murugan						✓				✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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