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RESEARCH AND EDUCATION

Application of 3D neural networks and explainable AI to classify ICDAS detection system on mandibular molars

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ABSTRACT

Statement of problem. Considerable variations exist in cavity preparation methods and approaches. Whether the extent and depth of cavity preparation because of the extent of caries affects the overall accuracy of training deep learning models remains unexplored.

Purpose. The purpose of this study was to investigate the difference in 3-dimensionsal (3D) model cavity preparations after International Caries Detection and Assessment System (ICDAS) classification performed by different practitioners and the subsequent influence on the ability of a deep learning model to predict cavity classification.

Material and methods. Two operators prepared 56 restorative cavities on simulated mandibular first molars according to 4 ICDAS classifications, followed by 3D scanning and computer-aided design processing. The surface area, virtual volume, Hausdorff distance (HD), and Dice Similarity Coefficients were computed. Multivariate analysis of variance was used to assess cavity size and operator proficiency interactions, and 1-way ANOVA was used to evaluate HD differences across 4 cavity classifications (α=.05). The 3D convolutional neural network (CNN) predicted the ICDAS class, and Saliency Maps explained the decisions of the models.

Results. Operator 1 exhibited a cavity preparation surface area of 360.55 ±15.39 mm^2, and operator 2 recorded 355.24 ±10.79 mm^2. Volumetric differences showed operator 1 with 440.41 ±35.29 mm^3 and operator 2 with 441.01 ±35.37 mm^3. Significant interactions (F=2.31, P=.01) between cavity size and operator proficiency were observed. A minimal 0.13 ±0.097 mm variation was noted in overlapping preparations by the 2 operators. The 3D CNN model achieved an accuracy of 94.44% in classifying the ICDAS classes with a 66.67% accuracy when differentiating cavities prepared by the 2 operators.

Conclusions. Operator performance discrepancies were evident in the occlusal cavity floor, primarily due to varying cavity depths. Deep learning effectively classified cavity depths from 3D intraoral scans and was less affected by preparation quality or operator skills. (J Prosthet Dent 2025;133:1333-1341)

Differences in operator technique and skill levels, encompassing variations in experience and proficiency, can lead to inconsistencies in cavity preparation techniques, depth, and overall quality.[1] Clinical judgment influences caries treatment; varied approaches highlight the need for standardized protocols and ongoing dental team

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Clinical Implications

Successfully classifying the extent and depth of dental cavity preparations using AI can lead to more unbiased treatment decisions. It is also a key step in automating 3D printed indirect restorations, potentially reducing the number of dental visits.

training.[2] Equipment variations, patient factors, and differences in materials and technologies also contribute to interoperator variability in cavity preparation outcomes.[3]

Classifying tooth cavities according to the International Caries Detection and Assessment System (ICDAS) presents challenges rooted in various factors.[4] The reliance on visual and tactile assessments introduces subjectivity, with different clinicians interpreting and assigning scores differently, leading to variability in cavity classification.[5] The detailed and nuanced scoring criteria of ICDAS, considering visual characteristics like color change and surface texture, can pose challenges, particularly for less experienced clinicians, resulting in inconsistencies.[6] These inconsistencies led to a shift toward more holistic approaches, with cavity design shaped by the lesion, introducing greater variability when training artificial intelligence (AI) in restorative dentistry. While AI favors standardization in learning, holistic approaches make this more challenging. As a result, despite the redundancy of caries classification systems in contemporary practice, a step back is necessary to reintroduce standardization for effective AI training.

Classifying cavities by their interproximal surfaces as per ICDAS cavity extent, where lesions may be concealed, is particularly challenging, and the use of radiographic imaging may introduce complexity and potential discrepancies.[6] The nonuniform progression of tooth cavities and variations in lesion activity may challenge clinicians in determining accurate classifications. Realistically, cavity preparations are unlikely to adhere strictly to the ideal ICDAS guidelines and introducing them to an AI model in such a rigid manner may not be practical. Instead, a semistructured system should be used that focuses on the core components of ICDAS such as depth and general extent while allowing for variations in proximal preparations.

Clinicians play an important role in the training and development of deep learning models, influencing both performance and generalization.[7] Clinicians curate training datasets, determine relevant features, refine model architecture, enhance interpretability, and guide model integration into clinical workflows for effective generalization. The ongoing participation in evaluation and refinement processes allows for model updates based on evolving clinical insights and data trends, thereby reinforcing the model's relevance in real world medical scenarios.[8,9] Despite these contributions, the inherent black box nature of AI and deep learning often poses challenges in extracting explanations for model predictions, prompting the exploration of model explainability or explainable AI aimed at enhancing the acceptance of AI models among professionals and community members.[10,11]

While considerable variations exist in methods and approaches to designing cavity preparations, an unexplored aspect pertains to whether the quality of cavity preparation affects the overall accuracy of training deep learning models.[12] Additionally, within the dental domain, research has yet to delve into the automated classification of tooth cavities from single-tooth 3-dimensional (3D) intraoral scans (Fig. 1). Such insights create avenues to objectively standardize the classification process through the integration of deep learning and model explainability, marking a significant step forward in advancing dental research and practice.

Therefore, the purpose of the study was to investigate the difference in 3D model cavity preparations loosely categorized through the ICDAS classification made by 2 practitioners and to determine whether the choice of practitioner can influence the ability of the deep learning model to successfully classify the cavity preparations. The null hypothesis was that the ability of the AI model to identify the type of cavity from 3D scans would not be significantly influenced by the clinician or the ICDAS classification.

MATERIAL AND METHODS

An in vitro experimental design of diagnostic test accuracy in machine learning followed the STARD 2015[13] and Nature Medicine MI-CLAIM 2021 guidelines.[14] To compare between 2 practitioners, a large effect size of 0.4[15] was considered adequate owing to previous reports of significant variability in operator decisions, α=.05, power = 0.95. A sample size of above 54 was found adequate for 2 groups and 4 independent sets of measurements. For the current study 2 clinicians (N.B.J., P.S.) with over 10 years of experience in restorative dentistry were recruited to simulate 56 cavity preparations, 28 each, to be divided equally across 4 classifications according to the International Caries Detection and Assessment System (ICDAS system) (Figs. 1 and 2).

The operators were instructed to create 7 standard cavities of progressively increasing cavity dimensions for each of the 4 ICDAS classifications (3, 4, 5, and 6). Instructions on the shape and size of the cavities were relayed through photographs of the expected

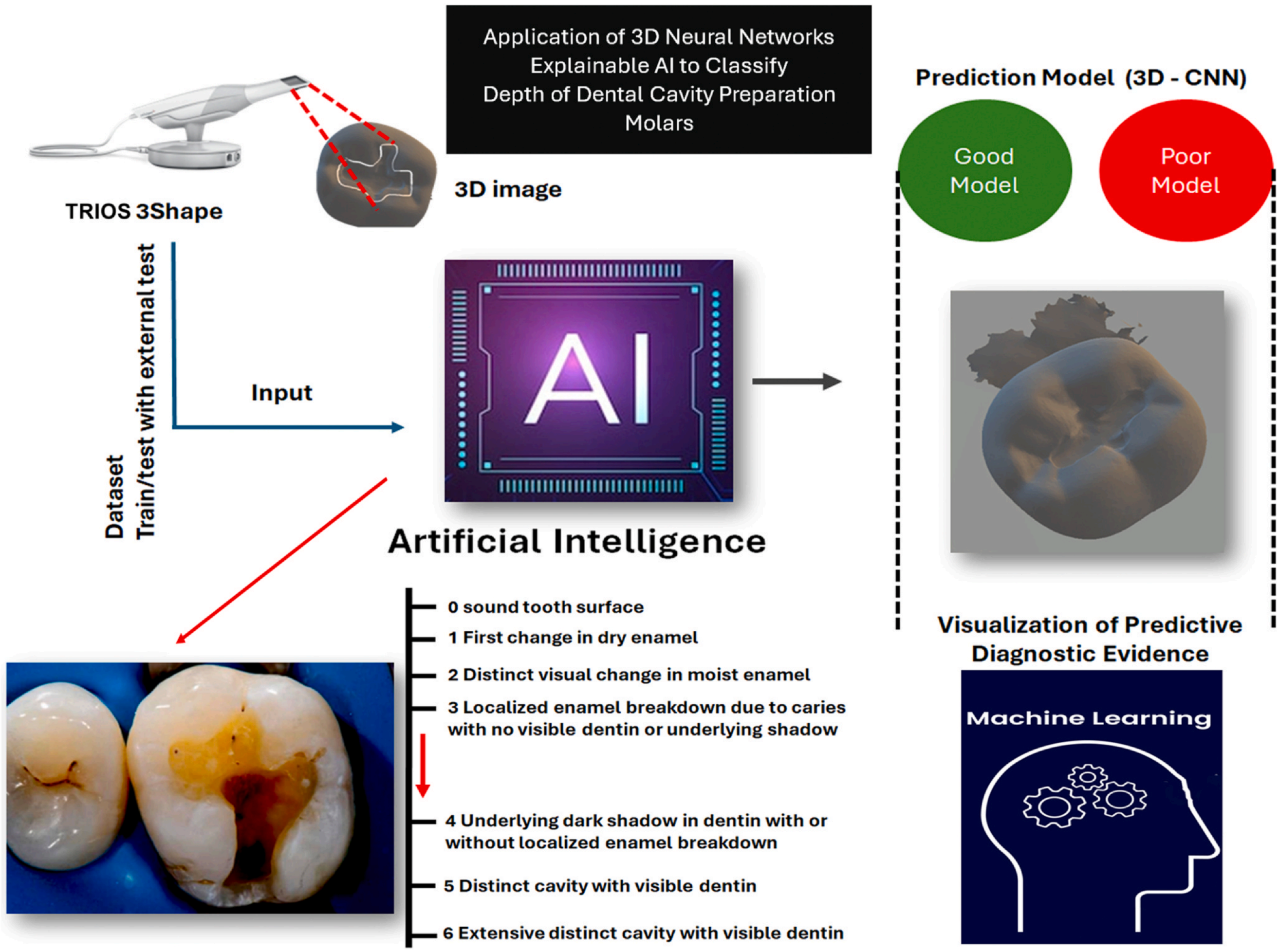

Figure 1. Flow chart of application of 3-dimensional neural networks with explainable artificial intelligence to classify depth of dental cavity.

preparation dimensions.[12] Typodonts (PVR 860; Columbia Dentoform Corp) were marked with ink to simulate the extent of caries appropriate for ICDAS classification by an independent practitioner (S.Z.Y.). The 56 composite resin cavity preparations were carried out on mandibular left first molars by following standard procedures.[16] The cavities were prepared by adhering to the principles of cavity design in the Sturdevant textbook.[17] Each cavity preparation was assessed for adherence to ICDAS design specifications while allowing for variations in the proximal boxes to account for clinical variability. Each preparation was evaluated by 2

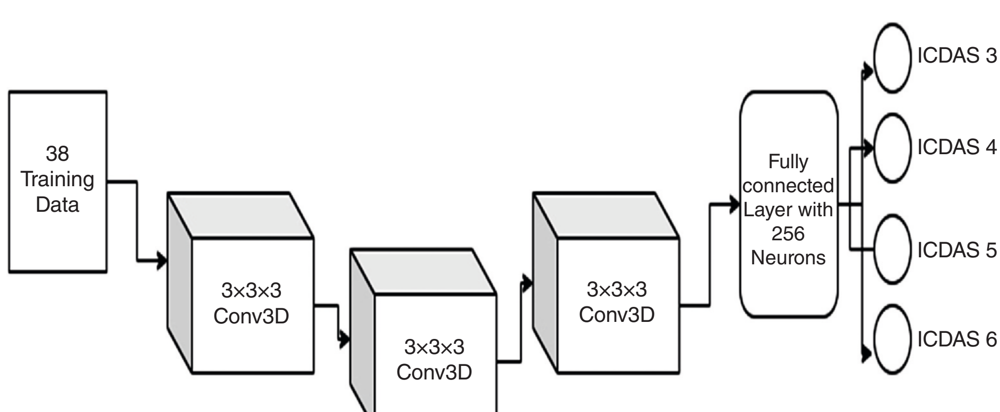

Figure 2. Workflow for deep learning to classify International Caries Detection and Assessment System cavities.

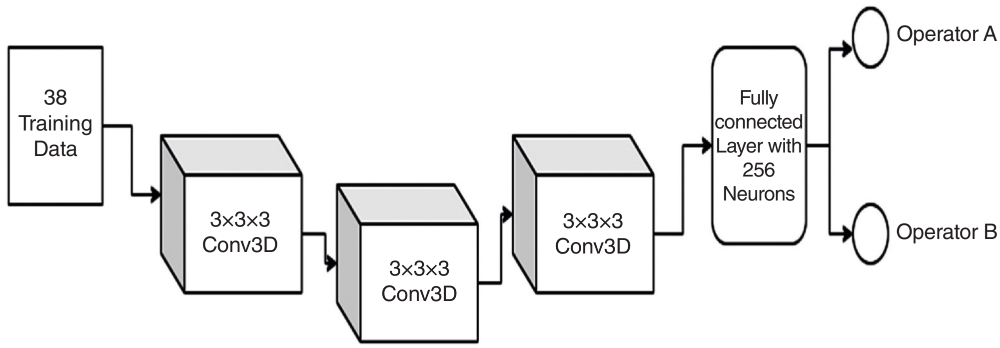

Figure 3. Workflow for deep learning to classify work performed by two operators.

dentists (P.K.P., U.D.) upon completion, with the evaluators being blinded to the identity of the clinician who prepared the cavity. The depths of the lesions were measured using a millimeter-marked probe (DuraLite ColorRings UNC #12; Nordent Manufacturing Inc) and maintained consistently across ICDAS classifications, with a maximum variation of 0.5 mm. If a tooth was designed outside the specification and permissible variation, the affected tooth was discarded, and the preparation remade. Once cavities had been prepared, the individual molars were removed from the typodont and 3D scanned by an investigator (P.K.P.) (Fig. 3).

The prepared teeth were 3D scanned using an intraoral scanner (TRIOS 3; 3Shape A/S) and exported as standard tessellation language (STL) files. The files were then corrected for mesh defects in a computer-aided design software program (Meshmixer; Autodesk Inc). To evaluate cavity differences across the 2 operators, the final 3D mesh files were analyzed in a 3D mesh processing software program (MeshLab; Visual Computing Lab)[18] to compute the tooth surface area, while cloud compare was used to evaluate the virtual volume, the Hausdorff distance (HD), and the Dice Similarity Coefficient (DSC). HD estimated the amount of dissimilarity of each point within the 3D mesh to its corresponding counterpart obtained from the other operator, while DSC computed the volume remaining after a Boolean intersection was performed when the 2 models were aligned and overlapped through the iterative closest point (ICP) algorithm.[19] As surface area and volume were interrelated for each cavity preparation, a multivariate analysis of variance was performed to evaluate the differences and interactions of surface area and volume across the different ICDAS classifications for each operator. This was followed by a 1-way analysis of variance to evaluate the differences in HD across the 4 ICDAS classifications for the 2 operators (α=.05).

A 3D convolutional neural network (3D-CNN) model architecture was then adopted for classifying 3D tooth images into 4 categories: ICDAS class 3, 4, 5, and 6.[12,20] It consisted of 3 convolutional layers followed by max-pooling operations to extract important features from the tooth images. The convolutional layers gradually increased in complexity, with the first layer having 16 channels, the second layer having 32 channels, and the third layer having 64 channels. Each layer used a 3×3×3 filter to maintain spatial dimensions. Max-pooling layers then down sampled the feature maps to extract key patterns. The model's output was processed through 2 fully connected layers for final classification, with a dropout layer included to prevent overfitting.

The convolutional layers extracted complex features from the 3D tooth images using convolution operations and rectified linear unit (ReLU) activation functions.[21] These features were then further refined through max-pooling layers to identify dominant patterns within the cavity. The fully connected layers processed these features for final classification. Additionally, dropout regularization helped enhance the model's generalization by randomly deactivating neurons during training. Detailed information on the implementation of the 3D CNN model and the codes used are available online through GitHub (https://github.com/aguynamedSaif/3D-ICDAS_based_tooth_classification).

The model was trained on a dataset of 38 teeth and evaluated on 18 additional teeth. Training was stopped early at 110 epochs to prevent overfitting.[22] A batch size of 2 was used, and the learning rate was set to 0.001 to adjust the model's learning based on the tooth images. Weight decay and momentum adjustments were applied to prevent the model from becoming too specialized on the training data.

The same model was applied to differentiate between corresponding ICDAS preparations made by the 2 different operators. The classifier was modified to distinguish between Operator A and Operator B instead of ICDAS classes. The details of the model architecture are shown in Figure 3. Saliency maps were used to extract justifications for the model's prediction process in classifying the different outcomes (Figs. 4 and 5).[23]

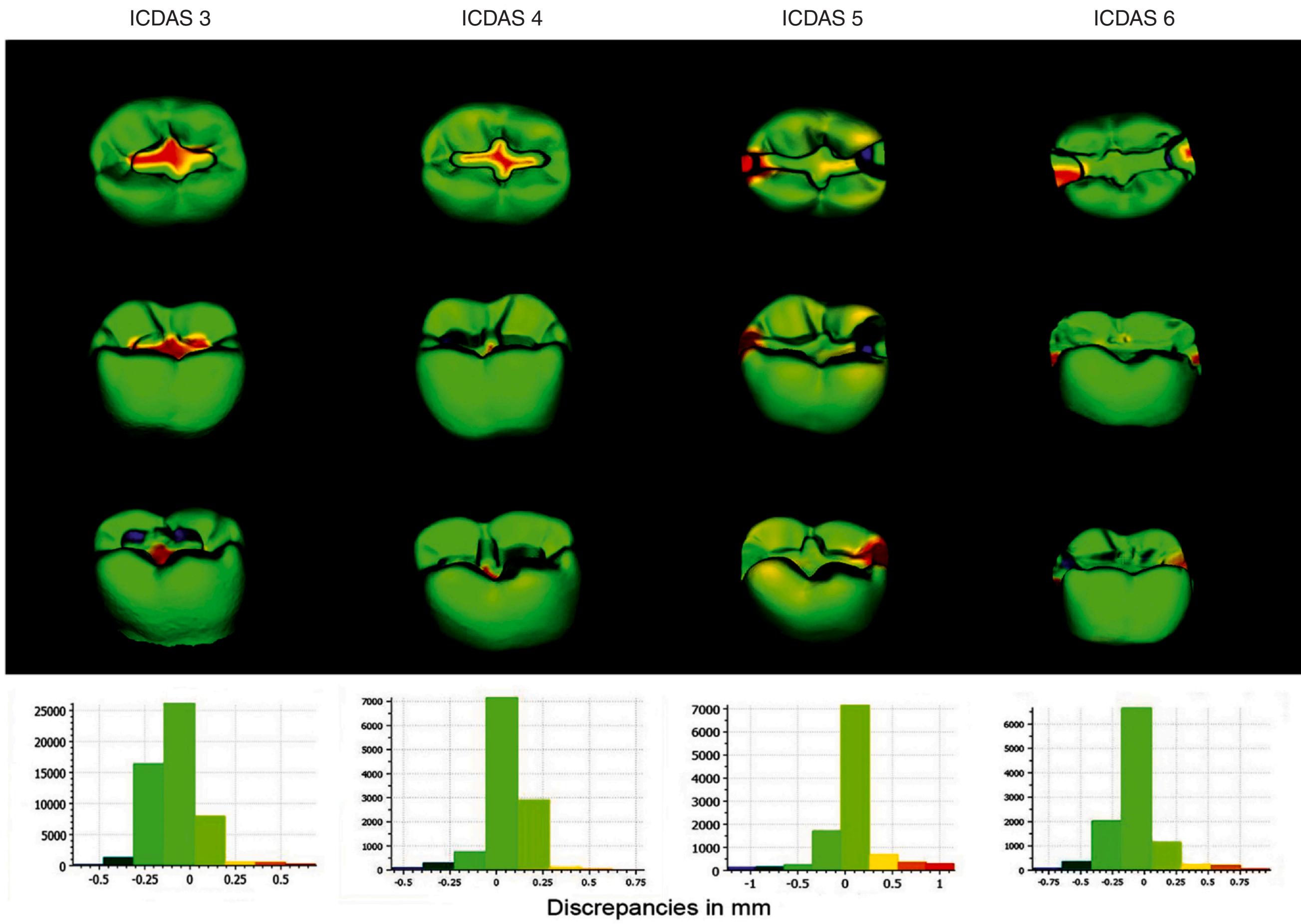

Figure 4. Visual representation of differences in preparation outcomes across different International Caries Detection and Assessment System classifications.

RESULTS

The initial analysis focused on the disparities in the mesh surface area of the cavity preparations performed by the 2 operators. Table 1 documents the mean and standard deviations of the mesh surface area and virtual volume for each type of classified cavity across both operators. Table 2 summarizes the multivariate analyses performed to identify the relationship between the operator's skill and cavity classification on the resulting cavity dimensions.

During HD evaluations, a minimal variation of 0.13 ±0.10 mm was noted in the preparations executed by the 2 operators when overlapping. Figure 4 provides a visual representation highlighting the key areas of discrepancies among the 4 ICDAS classifications. Notably, discrepancies were prominently observed on the floor of the occlusal boxes, primarily attributed to differences in the depth of cavity preparation. Additionally, discrepancies were noted at the point angles within the proximal boxes, emphasizing the nuanced aspects of cavity preparation that contributed to the observed variations. ANOVA outcomes for the HD of ICDAS classifications 3 (0.05 ±0.09 mm) and 4 (0.06 ±0.13 mm) demonstrated higher variations in discrepancies compared with ICDAS classifications 5 (0.07 ±0.03 mm) and 6 (0.07 ±0.03 mm). Table 3 demonstrates the findings from the analysis. DSC was consistently noted above 0.90 for all classifications. A detailed report of the internal validation outcomes has been documented in Supplemental Table 1–4 (available online).

The classification of the ICDAS model using the designed hyperparameters resulted in an accuracy of 94.44%. Saliency maps were used to extract explanations from the model regarding its decision-making process. In the first experiment, aimed at classifying between the four ICDAS classes, these maps illustrated that classifications were primarily based on the shape of the occlusal box, followed by the presence or absence of the proximal box, and, finally, the overall depth of the cavity.

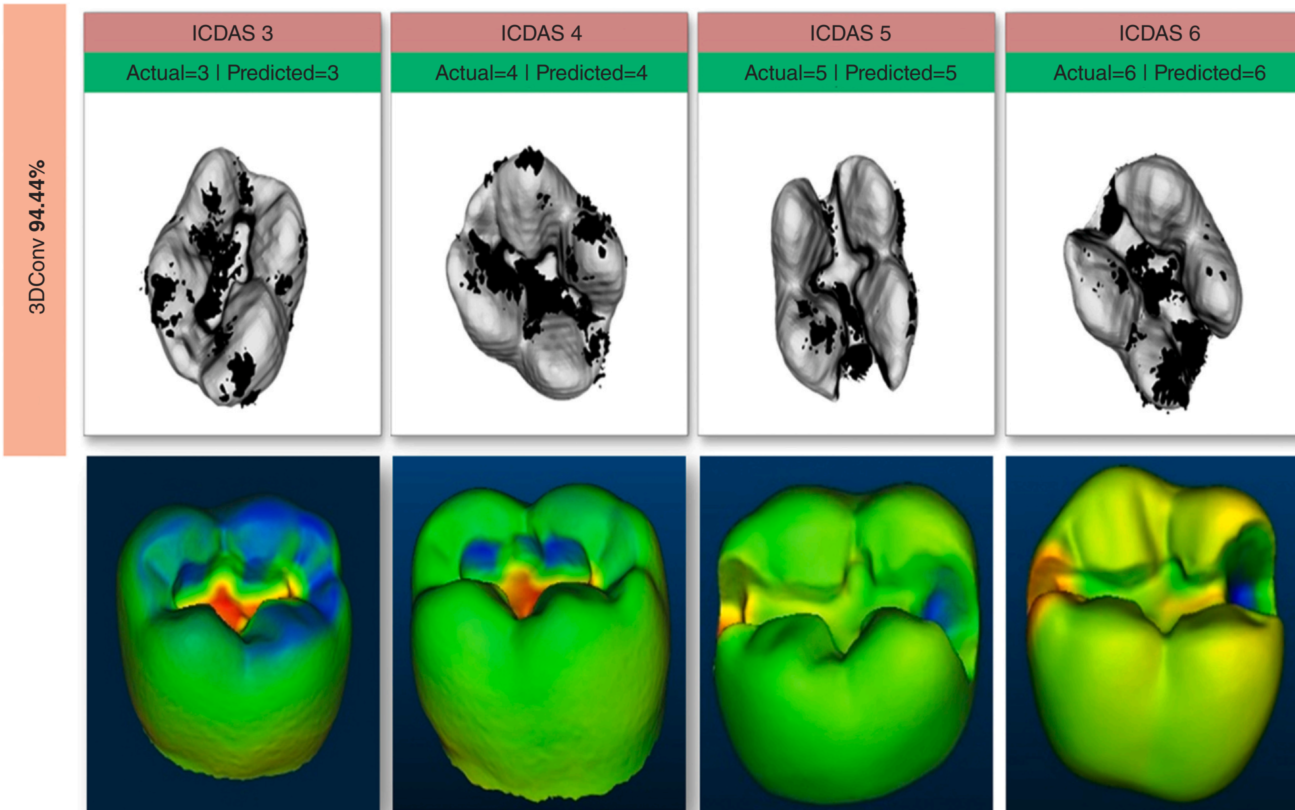

Figure 5. Saliency maps explaining regions of 3-dimensional models key to decision-making process when differentiating between International Caries Detection and Assessment System cavities.

Table 1. Mean ±standard deviations of mesh surface area and virtual volume for cavity classification and operator variability

Cavity Classification Across Both Operators		Mesh Surface Area (mm^2)	Virtual Volume (mm^3)
ICDAS 3		367.48 ±12.41	466.74 ±41.76
ICDAS 4		365.01 ±12.66	436.83 ±43.25
ICDAS 5		354.35 ±6.66	428.46 ±15.83
ICDAS 6		344.76 ±7.27	430.81 ±17.57
Individual operator across each cavity classification			
		Mesh Surface Area (mm^2)	Virtual Volume (mm^3)
Operator 1	ICDAS 3	375.92 ±14.35	471.36 ±41.18
	ICDAS 4	369.36 ±4.89	443.37 ±18.12
	ICDAS 5	355.61 ±8.01	430.01 ±16.57
	ICDAS 6	343.44 ±4.59	434.69 ±15.09
Operator 2	ICDAS 3	361.14 ±5.66	463.28 ±44.66
	ICDAS 4	361.74 ±15.88	431.92 ±56.36
	ICDAS 5	353.40 ±5.83	427.29 ±16.30
	ICDAS 6	345.50 ±8.57	428.64 ±19.32

ICDAS, International Caries Detection and Assessment System.

Differentiations between ICDAS 3 and 4 were scrutinized more closely by the model, which attempted to analyze the entire occlusal box, including the line and point angles, before generating a prediction.

The achieved accuracy was 66.67% when comparing preparations performed by the 2 practitioners. Saliency maps reveal seemingly random areas of prediction that correlated with areas of bur-induced nicks and roughness performed by the operators during the preparation process. In the presence of the significant differences across the multivariate analyses, the 66.67% accuracy would suggest that prediction accuracies were largely unaffected by the significant operator biases and variations in cavity preparations. The saliency maps (Fig. 6) demonstrate that, when necessary, the model was able to detect nuanced differences between the operators.

DISCUSSION

The current study investigated whether the clinician or the classification of ICDAS cavity preparation would significantly influence the AI model's ability to identify the type of cavity from 3D scans. Significant differences in 3D mesh surface area and volume were observed, along with interactions across clinical operators and cavity classifications. Therefore, the null hypothesis that the ability of the AI model to identify the type of cavity from 3D scans would not be significantly influenced by the clinician or the ICDAS classification was rejected.

Significant differences in mesh surface areas and volume were observed both statistically and visually across cavities prepared by the 2 practitioners, with most

Table 2. Outcomes for analysis of variance of mesh surface area and virtual volume

Source	Test statistics	Value	F-value	Df (Numerator, Denominator)	P
Cavity classification	Pillai Trace	0.77	10.02	3 (6, 96)	<.001*
	Wilks Lambda	0.33	11.64	3 (6, 94)	
	Lawley-Hotelling trace	1.73	13.30	3 (6, 92)	
	Roy largest root	1.54	24.61	3 (3, 48)	
Operator	Pillai Trace	0.18	5.12	1 (2, 47)	.001*
	Wilks Lambda	0.82	5.12	1 (2, 47)	
	Lawley-Hotelling trace	0.22	5.12	1 (2, 47)	
	Roy largest root	0.22	5.12	1 (2, 47)	
Interaction between cavity classification and operator	Pillai Trace	0.25	2.31	3 (6, 96)	.01*
	Wilks Lambda	0.76	2.34	3 (6, 94)	
	Lawley-Hotelling trace	0.31	2.37	3 (6, 92)	
	Roy largest root	0.26	4.22	3 (3, 48)	

*Significant (*P*<.05).

Table 3. Analysis of variance of Hausdorff distance evaluation across International Caries Detection and Assessment System classifications

	Sum of Squares (df)	Mean Square	F value	P
Between Groups	0.06 (3)	0.02	2.152	.120
Within Groups	0.20 (24)	0.01		
Total	0.26 (27)			

Significant (*P*<.05).

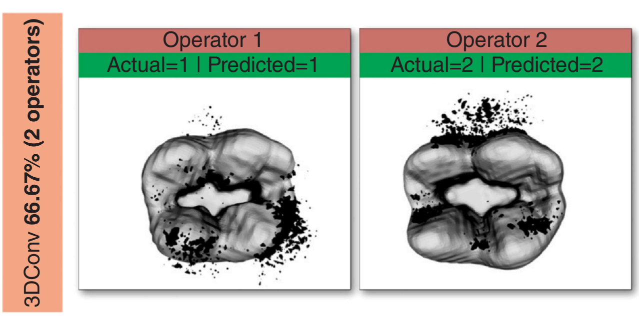

Figure 6. Saliency maps explaining regions of 3-dimensional models key to decision-making process when differentiating between International Caries Detection and Assessment System cavities.

discrepancies found on the floor of the occlusal boxes and point angles. The overall form of the cavities, however, remained unchanged as demonstrated by the statistical evaluation of the Hausdorff distance.

Deep learning was capable of disregarding operator-dependent variables such as the quality of cavity preparation in favor of focusing on the general shapes of the occlusal and proximal boxes and the depth of the lesion, resulting in high accuracy. The relatively lower accuracy in distinguishing between the preparations of the practitioners could stem from the effective identification of clinical proficiency, rather than the specific shape and form of the cavities. The model demonstrated an ability to overlook the nuances of the preparation and concentrate on the essential characteristics, rendering it robust and versatile for various clinical settings.

The findings of the current study yielded better results from 3D scans compared with a previous in vivo report reporting 82.80% accuracy that used deep learning to identify lesions from intraoral images.[24] However, the current study relied on simulated tooth preparations carried out within a controlled environment, devoid of saliva or surface reflection. This, however, may not be pertinent in 3D imaging, which emphasizes the third dimension of depth when formulating predictions. Extracting carious lesions from dental radiographs has become a more straightforward process, owing to the identification of areas of radiolucency within a grayscale overall image and explainable through heatmaps.[25,26] However, this is not the case in vivo, where tooth shades vary substantially under different lighting conditions and in different patients and remains a topic for future investigation.

Previous investigations used the international caries detection and assessment system (ICAD) to evaluate and categorize the extent of dental caries when occlusal images were employed as an input source.[27,28] The research analyzed in this review relied on image assessments conducted by ICAD experts or experienced clinicians. The authors are aware of only 1 study that correlated visual assessment with histology.[29] CNNs have demonstrated a precision rate of 95.8% to 99.45% in detecting and identifying teeth, almost rivaling the work of clinical experts, whose precision rate was 99.98%.[30] This is a considerable improvement over diagnosis by clinicians using radiographs alone, with sensitivity varying from 19% to 94%.[31] Deep CNNs have great potential for improving the sensitivity of dental caries diagnosis and, this, combined with their speed, makes them efficient tools. The performance of AI design did not significantly differ from that of human design, and the AI design of dental cavities has considerable clinical feasibility.

Limitations of the model explainability of the 3D dataset included that the complexity of cavity preparations presented in multiple layers posed articulatory challenges for prediction models to provide clear and interpretable explanations for their predictions. The absence of standardized methods for explaining AI predictions means that, unlike the conventional image reporting methods globally adhered to, most early adopters of medical AI use their own methods of interpreting model explainability charts and maps.[32] This results in subjective interpretations among clinicians, with an overarching possibility of sacrificing superior performance from more complex unsupervised models in favor of transparency that would foster greater interoperator agreements. Finally, given the current logistical constraints and the highly variable nature of 3D AI, a sample size that may limit the generalizability to the target population was used.

Psychosocial factors like performance expectancy, usefulness, and trust influence AI technology acceptance. Further research and theory building are recommended to understand user attitudes in relation to model explainability.

CONCLUSIONS

Based on the findings of this in vitro study, the following conclusions were drawn:

1. Despite significant statistical differences in the evaluations across ICDAS caries extension and cavity dimensions, the 3D neural networks successfully classified cavity preparations. This was achieved even though the 3D models showed notable statistical differences among themselves and were less affected by the preparation quality, which was influenced by operator skill.
2. Physical discrepancies in operator performance were evident on the floor of the occlusal cavity box, primarily due to variations in cavity depth.
3. Variations at point angles in proximal boxes also impacted model predictions.

ETHICS STATEMENT

All experimental protocols were approved by the Joint Ethical Committee/ Institutional Review Board under Project No. 259/2020. The models applied and the methodologies developed were derived as a part of a research project approved by the University Human Research Ethics Committee (H-2023–073) and Institutional Review Board at University (2023/OR-NSU/IRB/0503). The ethical committee at International Medical University approved the study, protocol (IMU IA641).

APPENDIX A. SUPPORTING INFORMATION

Supplemental data associated with this article can be found in the online version at doi:10.1016/j.prosdent.2024.09.014.

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CRediT authorship contribution statement

Taseef Hasan Farook: Conceptualization, Data curation, Formal analysis, Methodology, Roles/Writing - original draft. **Saif Ahmed**: Conceptualization, Data curation, Formal analysis, Writing - review and editing. **Farah Rashid**: Investigation, Resources. **Faisal Ahmed Sifat**: Investigation, Methodology, Software. **Preena Sidhu**: Methodology, Writing - review and editing. **Pravinkumar Patil**: Methodology, Project Administration, Validation. **Sumaiya Zabin Eusufzai**: Data curation, Validation, Writing - review and editing. **Nafij Bin Jamayet**: Data curation, Formal Analysis. **James Dudley**: Visualization, Writing - review and editing. **Umer Daood**: Conceptualization, Funding acquisition, Project Administration, Supervision, Writing - review and editing.

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