

A Novel Optimized Hybrid ResNextTransform for Dental Diseases Classification with Crested Porcupine Optimizer

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Abstract

Artificial intelligence is revolutionizing healthcare by assisting medical professionals with disease prediction, diagnostic procedures, and efficient treatment planning. Deep learning has emerged as a revolutionary technology in contemporary dentistry, which can handle dental images efficiently and produce accurate diagnostic results without human intervention. Traditional deep learning models lack generalizability, accuracy, and interpretability of local features and global interaction. Here, the hybrid ResNextTransform model with grouped convolution is developed to classify various dental disorders, and the metaheuristic Crested Porcupine optimizer (CPO) is employed to optimize the hyperparameters. The proposed model is used to classify the dental images into caries, calculus, gingivitis, tooth discoloration, ulcers, and hypodontia. The ResNextTransform model achieves 95.9% accuracy, 95.4% sensitivity, 95.7% precision, 95.2% AUC, 95.5% specificity, and 95.1% F1-Score. The performance of the model significantly improves with CPO optimization and produces 97.3% accuracy, 97.4% sensitivity, 97.2% precision, 97.2% AUC, 96.9% specificity and 97.1% F1-Score.

Keywords: Dental Diseases, ResNext Transform, Crested Porcupine Optimizer, Classification.

1. Introduction

Dental caries is the widespread dental disorder popularly known as cavities, produced by bacterial infection, which has various stages, from initial to moderate and deeper levels [1]. Dental calculus within the oral cavity is a calcified dental biofilm that firmly bonds to the surfaces of dental prostheses and natural teeth [2]. Gingivitis is primarily caused by the accumulation of bacterial biofilm from dental plaque, which eventually progresses to periodontitis if left untreated [3]. Tooth color plays a vital role in reflecting the social status of

people, and as individuals grow older, the color of their teeth changes to yellow and red tones [4]. Mouth ulcers in the oral cavity are painful lesions that affect 20% of the population globally [5]. Hypodontia is a condition involving one or more missing teeth, inherited genetically from one of the parents [6].

Artificial intelligence plays a vital role in achieving revolutionary transformation in contemporary dentistry and has a substantial impact on patient care and effective treatment planning [7]. The impetus for this research stems from the pressing need to precisely improve the diagnostic accuracy of various dental diseases with overlapping features in radiographic images. This last few decades have witnessed a revolution in medical diagnostics with Machine Learning (ML) and Deep Learning (DL) leading the way in medical image diagnostics [8]. The revolutionary surge has also made significant inroads into the field of dentistry [9]. The growing abundance of dental X-rays has accelerated the application of ML algorithms in this field. In particular, Convolutional Neural Networks (CNNs) have gained significant popularity due to their exceptional ability to learn and interpret from complex, latent patterns [10]. Their rapid development and ability to extract vital information ambiguous medical images make them ideal for identifying unnoticed dental issues [11].

Motivated by the untapped potential of uncharted feature extraction techniques in dental image analysis, this work investigates techniques that have not been incorporated in this domain. When properly leveraged, these approaches can unveil valuable and meaningful insights from dental X-rays. To address the shortcomings of current diagnostic methods and obtain a comprehensive view, we employ a fusion strategy that complements the strengths of varied approaches.

In this work, we propose a hybrid framework that integrates ResNext and Transformer, drawing on their complementary capabilities to enhance feature extraction from radiographs for classifying various dental diseases. ResNext, by utilizing parallel transformation paths, enhances feature extraction by capturing rich features with only an increase in depth or width. It is capable of learning intricate features and complex textures with few parameters. Transformers offer powerful feature extraction by focusing on global relationships with their self-attention mechanism. They better in identifying subtle patterns and long-range dependencies, supporting better generalizability over CNN models. Metaheuristic algorithms offer several advantages compared to conventional optimization techniques utilized in CNNs in the literature. They possess a strong global search capability and can escape from local minima, unlike gradient-based techniques. The deployment of CNNs encounters many issues related to reliability and comprehensibility, suggesting challenges with black box testing. There is a noticeable gap in the current literature regarding optimization. To improve model efficacy in healthcare imaging from a clinical standpoint, this study integrates the Crested Porcupine Optimizer (CPO) algorithm for CNN parameter tuning.

2. Related Work

Dental informatics is a relatively new area in the field of dentistry that assists dental practitioners by reducing their stress and saving time. The incorporation of Artificial Intelligence constitutes a major progression in the pivotal advancement of dental diagnostics. Convolutional Neural Networks (CNN) are the most widely used deep learning models for image classification in dentistry.

2.1 Image Processing-Based Methods

Image processing-based feature extraction techniques are combined with machine learning to detect and classify dental cysts from panoramic dental X-rays [12]. Two-stage SVM models were constructed for classifying osteoporosis from dental panoramic X-rays, and the work produced better results with Histogram of Oriented Gradient features [13]. Texture-based features are extracted using Laplacian filters for image enhancement, the Grey Level Co-occurrence Matrix is utilized for extracting texture features, and SVM is finally used to classify dental caries using the extracted features [14]. A Gaussian low-pass filter is incorporated to extract features in the frequency domain, and the extracted features of caries are classified using SVM. GLCM is used to extract textural features, which are classified using SVM and KNN algorithms [15]. Caries images are classified from healthy images where textural features were extracted using GLCM, GLRLM, and LBGLCM [15]. Machine learning based Modified Local Binary Pattern (MLBP) is used to extract textural features and is classified using KNN, SVM, and decision tree classifiers [16].

2.2 Deep Learning-Based Methods

Deep learning based EfficientNet classifiers are used to classify various dental disorders like caries and periodontitis using periapical radiographs [17]. The InceptionResNetV2 model is used to classify various oral cancers and mouth diseases and produces significantly higher accuracy, but this model lacks generalizability [18]. Hypodontia is detected using various pretrained deep learning-based CNN models for training with fine-tuning, along with machine learning classifiers, where VGG-19 coupled with bilayered neural networks produces the best results [19]. A multiple-input deep CNN model is used to classify dental caries from CBCT dental images [20]. A pretrained VGG16 model is used to classify periodontitis, dental caries from RVG images and periapical infection in 35 epochs [21]. A rank-based fuzzy non-linear ensemble model combines the benefits of various deep learning-based CNN models to classify various dental diseases using color images [22]. The Retinex algorithm is designed to enhance dental images, and a lightweight CNN is developed to classify periapical lesions from CBCT scans [23].

2.3 Optimization Techniques

Metaheuristic algorithms have emerged as an alternative to conventional gradient-based techniques, especially in medical image processing, where data is multimodal, high-dimensional, and the search space is non-differentiable. Particle Swarm Optimization (PSO) is widely incorporated in fine-tuning various continuous hyperparameters like momentum, learning rate, and the number of hidden neurons. It also provides convergence stability by balancing local and global exploration [24]. Ant Colony Optimization (ACO) is a good fit for solving discrete problems with less complex deep learning models. It is suitable for network pruning, feature selection, and making changes in architectural design [25]. Grey Wolf Optimization (GWO) provides a balance between exploitation and exploration mechanisms, and it has gained popularity in recent times in optimization that feature selection, and activation function selection [26]. CPO is a recent metaheuristic optimization, which simulates the defensive quill firing behavior and foraging behavior of porcupines. It is a lightweight algorithm that converges faster and has high stability by escaping from local minima [27].

3. Materials and Methods

3.1 Data Set Description

High quality, reliable datasets play a vital role in developing robust deep learning models. The dental condition dataset comprises an extensive collection of RGB images, assembled specifically for researchers in the field of dentistry. The dataset focuses on numerous dental disorders, including caries, gingivitis, tooth discoloration, hypodontia, calculus, and ulcer. It serves as an invaluable tool for researchers, dental practitioners, and machine learning professionals [28]. The dataset consists of labeled images in each of these categories, as shown in Figure 1. The train, validation and test sets are split in the ratio of 70%, 20% and 10%, respectively, and the distribution of the images in each category is shown in Figure 2. Geometric and photometric data augmentation techniques are applied to improve the generalizability of the models. The augmentation techniques include rotation $\pm 15^\circ$, horizontal flip, random crop, scaling (0.8–1.2), and brightness and contrast adjustment. In total, there are 10,735 images covering six different categories. During inference, test-time augmentation was employed to improve prediction robustness. For each test image, multiple augmented versions were generated using various geometric and photometric augmentation techniques. Five augmented variants are generated per image along with the original image and predictions are performed.



Figure 1. Random Images from Each Class

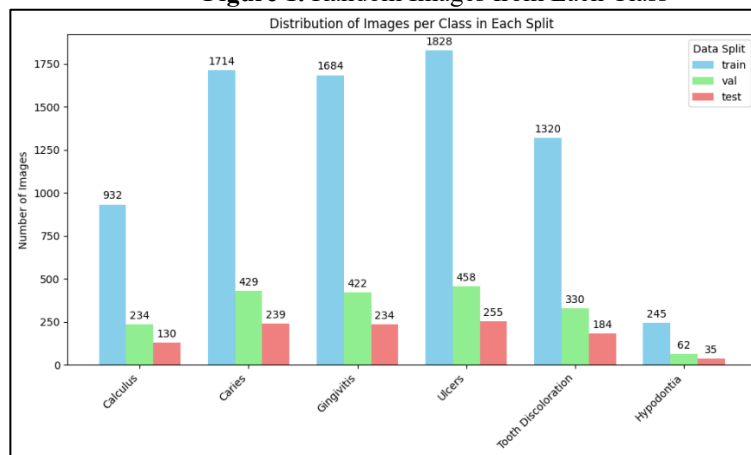


Figure 2. Image Distribution in Each Split

3.2 Methodology

This research proposes a novel hybrid deep learning architecture that leverages the complementary advantages of ResNext and Transformer models, optimized using the Crested

Porcupine Optimizer (CPO), for multiclass dental disease classification, specifically targeting diseases in RGB dental images. Multiclass image classification in the medical domain necessitates powerful feature extraction and attention mechanisms to handle complex textures and nuanced differences between various disease classes. ResNext employs grouped convolutions and parallel processing to capture the spatial features with less computational demand. The architecture is also flexible and scalable, allowing the blocks to be stacked easily with the split, merge and transform strategy. It is also efficient in capturing the rich and diverse features of complex images. Transformers have the ability to capture global dependencies and identify the relationships between distant elements in the data. They focus on important areas of the input, contributing to better comprehension. This also accelerates training and inference by processing all data at once. Conventional gradient-based optimization poses challenges in problems associated with discrete variables and leads to sub-optimal convergence, which is reduced by CPO. CPO is preferred over Bayesian optimization since it has superior scalability and resilience in high-dimensional and noisy environments. It performs derivative free global search in contrast to Bayesian optimization which has more computational overhead [29]. Learning rate, patch size, weight decay, dropout, epochs, and steps per epoch are the hyperparameters optimized by CPO.

3.2.1 ResNextTransform

The proposed ResNextTransform deep learning model is a hybrid model designed based on inspiration from ResNext and Transformer. The ResNextTransform model aims to combine the efficiency of CNNs with transformers. The ViT-B/16 Model with 12 layers, 768 dimensions, and 12 attention heads is used for comparative analysis with CNNs. The model is pretrained on the ImageNet dataset, which accelerates the training and is further fine-tuned for the target dataset. ResNext evolved from ResNet which is most suited to tasks based on computer vision. It is based on the idea of split, transform and merge, which is a simplified concept borrowed from the inception technique. The input path is divided into various parallel branches. A transform is applied to each path by utilizing small convolutions. Then, individual paths are merged to produce the final output. This increases the cardinality and is comparatively simpler than deeper and wider models. It also avoids the vanishing gradient problem with residual connections. Here, ResNext is used as a backbone with four stages and produces a feature map of length 2048. The transformer blocks are then included to produce a feature map of length 1024. The feature dimension of 1024 reduces computational cost and memory compared to 2048 feature dimensions, lowering the dimensional space and reducing training time. The features are then classified using a softmax layer. The input RGB image with 3 channels, height h , and width is extracted using ResNext.

ResNext employs the summation of several parallel group convolutions by extending ResNet

Preliminary Convolution Operation:

$$f_{resnext} = f_{in} + \sum_{x=1}^g t_x(f_{in}) \quad (1)$$

This is the fundamental ResNext identity shortcut plus aggregated transformations.

The backbone network reduces the spatial resolution by a factor of 32 after downsampling high-quality dental images from 2048x2048 to 1024x1024, producing a 7x7

feature grid. This approach maintains computational efficiency while preserving clinically relevant spatial context.

The final output:

$$f_{cnn} \in r^{2048 \times 7 \times 7} \quad (2)$$

Channel Projection is done where 1X1 convolution is performed where 2048 channels are projected into 1024 channels

Where

$$X_b \in r^{2048 \times 7 \times 7} \quad (3)$$

Hence

$$f_{prj} \in r^{1024 \times 7 \times 7} \quad (4)$$

Flatten and position encoding

49 (7X7) spatial grids are reshaped

$$S_p = Flat(f_{prj}) \in r^{49 \times 1024} \quad (5)$$

The 7×7 feature map is projected to 1024 channels, which are flattened into a sequence of 49 tokens, each representing a fixed spatial location in the original grid. To preserve the spatial information, a learned positional encoding of size 49×1024 is added elementwise to the flattened features. This position-aware representation is then passed to the subsequent modules, enabling the model to reason about spatial relationships despite the sequence-based formulation.

3.2.2 Crested Porcupine Optimization Algorithm

Deterministic optimization algorithms produce the same output for a given input. They also suffer from multiple local optima, which is overcome by metaheuristic optimization algorithms. Porcupines are independent creatures that use their sharp quills for self-defense and to protect themselves against the external environment. The Crested Porcupine Optimizer is a revolutionary metaheuristic optimization algorithm designed with inspiration from nature. Crested porcupines perform threat assessments by expanding their area of expansion. It avoids premature convergence by broadly exploring the search space.

Step 1: Population Initialisation

Initialise a population of porcupines $P = \{Y_1, Y_2, \dots, Y_n\}$ and determine the fitness $f(Y_i)$ value of each porcupine.

The initial solutions are produced consistently within the boundary.

$$Y_{ab} = Lo_b + ran(0,1)(Up_b - Lo_b) \quad (6)$$

Where Lo_b represents the lower bounds and Up_b represents the upper bounds.

Fitness value of individual porcupines are computed

$$F(Y_a) = Obj(Y_a) \quad (7)$$

Determine the current best porcupine

$$Y_{cbest} = argmin F(Y_a) \quad (8)$$

Step 2: Exploration Phase (Defensive Phase)

Porcupines investigate new regions while foraging in small groups. They explore uncharted territory in search of food. This is consistent with their cautious defensive movement, during which they make erratic movements to evade danger.

The exploration behaviour of porcupines is

$$Y_a^{x+1} = Y_a^x + \beta \cdot ran(-1,1)^v \quad (9)$$

Where β represents the step size of exploration and $ran(-1,1)^v$ represents a random vector.

When the porcupines distance themselves, repulsive exploration is performed.

$$Y_a^{x+1} = Y_a^x + \beta(Y_a^x - Y_b^x) \cdot ran(0,1)^v \quad (10)$$

Where Y_b represents a random porcupine, and β represents the repulsive strength.

Early convergence is prevented by providing diverse solutions with an enhanced global search.

Step 3: Exploitation Phase (Foraging Phase)

The position of the porcupine is updated during each iteration. The best current individual is determined among all the porcupines. During this phase, the best current individual is determined. Here, the movement is governed by attractive forces and step size parameters.

Using the foraging behavior, CPO updates the position of each porcupine. It focuses on the current best instead of a new area.

$$Y_i(a+1) = Y_i(a) + ran \cdot (Y_{best}(a) - Y_i(a)) \quad (11)$$

Where $Y_i(a)$ represents the present porcupine position at ath iteration, $Y_{best}(a)$ is the best position of the individual, ran is the random factor for balancing the diversity.

It avoids premature convergence and avoids getting trapped in a local minima.

Step 4: Fitness Evaluation

After the exploitation phase, the fitness of each porcupine is updated

Fitness function

$$F_i = Fit(Y_i) \quad (12)$$

Step 5: Global Best updation

The fitness value of each porcupine is compared with the best current best solution. Update the best porcupine based on the fitness value.

$$Y_{Best} = Y_i, \text{ if } F_i < F_{Best} \quad (13)$$

Crested Porcupine Optimization Algorithm

Input:

Population size A, Objective function g(y), Maximum Iterations M

Output:

Best Solution Y_{best} with optimal features

1. Randomly initialize a population $Po = \{Y_1, Y_2, \dots, Y_n\}$ within a search space, where Y_i represents ResNextTransform hyperparameter set.
 2. Determine the fitness $f(Y_i)$ for each porcupine P_i in Po .
 3. Train ResNextTransform for the dental diseases dataset
 3. Initialize each personal best porcupine $P_i = Y_i$ and global best $GO = \text{best of } P_i$ to optimize the ResNextTransform features
 4. Repeat for each iteration $i=1$ to M
 - For each porcupine P_i in Population P_i
 - Forage: Navigate to achieve solutions by applying randomness
 - Defend: Return to P_i if the fitness value falls below threshold
 - Compute the value of $f(Y_i)$
 - Update the local best of P_i if $f(Y_i)$ improves
 - Update the Global best G by choosing the best solution from P_i
 - Adjust the values of defensive strength and foraging radius
 5. Evaluate the fitness function of CPO optimizer for the ResNextTransform features R_i

$$Fitness = \gamma CaLoss + \alpha(1 - acc), \gamma + \alpha = 1$$

CaLoss – Categorical cross entropy loss, acc – Multiclass accuracy, γ & α – weighted coefficients
 6. Return the best global value G as optimal features for ResNextTransform
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3.2.3 ResNextTransform with CPO

The architecture diagram of ResNextTransform with CPO is depicted in Figure 3. The parameters of ResNextTransform are optimized using CPO. The CPO stops when the maximum number of iterations is reached, or the objective (fitness) between consecutive iterations falls below a predefined threshold, indicating convergence. The search space for CPO is defined by bounded ranges for each optimized hyperparameter, selected to ensure stable and meaningful exploration:

- Learning rate: $[1 \times 10^{-6}, 1 \times 10^{-3}]$
- Patch size: $\{4, 7, 16\}$
- Weight decay: $[1 \times 10^{-7}, 1 \times 10^{-5}]$
- Dropout rate: $[0.1, 0.6]$
- Epochs: $[25, 100]$
- Steps per epoch: $[6, 60]$

All candidate solutions are constrained within these bounds, and the configuration with the best fitness value is used for final model training.

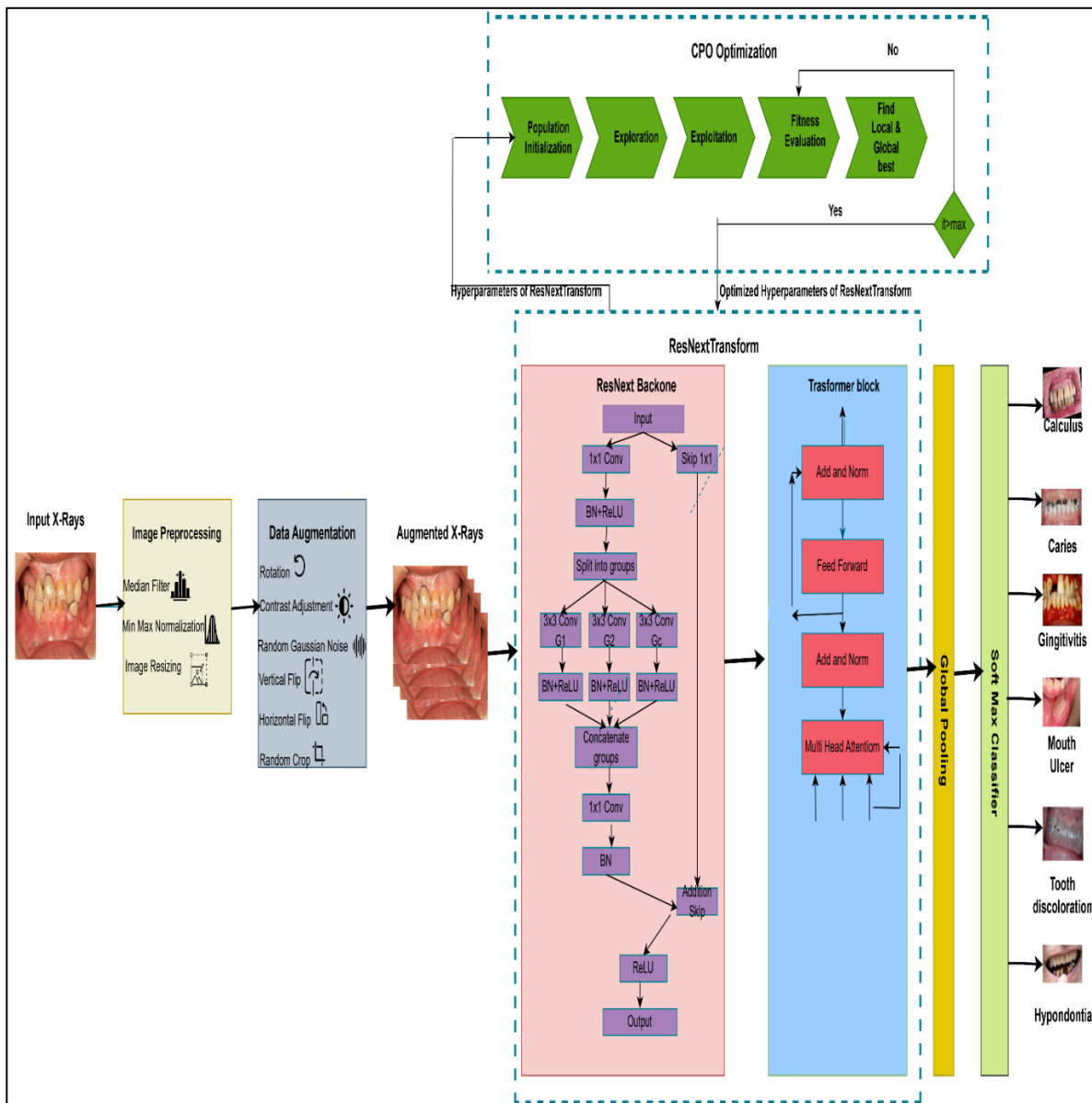


Figure 3. Architecture Diagram of ResNextTransform with CPO Optimization

4. Results and Discussion

The proposed system comprises hybrid ResNext and Transformer blocks for extracting the essential features from colored dental images. In this work multiclass classification is performed using a softmax classifier to distinguish six dental disorders. Here, a weighted cross-entropy loss function is employed for training the model using backpropagation. The hyperparameters that are essential for tuning the proposed classifier are optimized using the metaheuristic CPO optimization algorithm, which selects the optimal parameters for training the suggested model, as displayed in Table 1. Patch size affects performance because of the trade-off between computational efficiency and spatial detail. The optimal balance is achieved

with a 4×4 patch size, which captures fine-grained features without over-tokenization, leading to superior performance across all performance metrics.

Table 1. Hyperparameters for the Suggested Classifier

Hyperparameters	ResNextTransform
Learning rate	0.0001
Patch Size	7X7
Weight decay	1×10^{-6}
Dropout	0.1
Epochs	50
Steps per epoch	10

The loss and accuracy curves are shown in Figure 4. Here, the weighted cross-entropy loss function is employed using backpropagation to train the proposed model, which starts to converge smoothly after 35 epochs and provides better accuracy at 50 epochs.

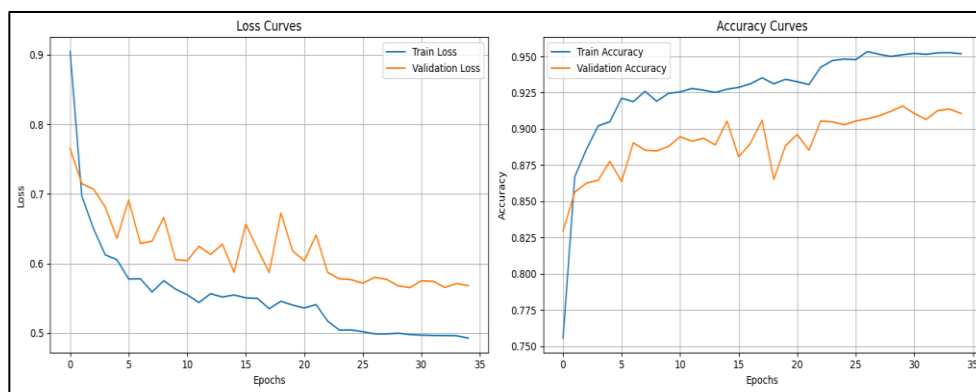


Figure 4. Loss and Accuracy Curves of the Proposed Work

Precision and recall curves of the proposed work are depicted in Figure 5. This work produces high precision; hence, the model avoids unnecessary therapies for patients by reducing false positive dental disorders. A higher value of recall implies that the patients affected by various dental disorders are correctly identified thereby reducing false negative cases.

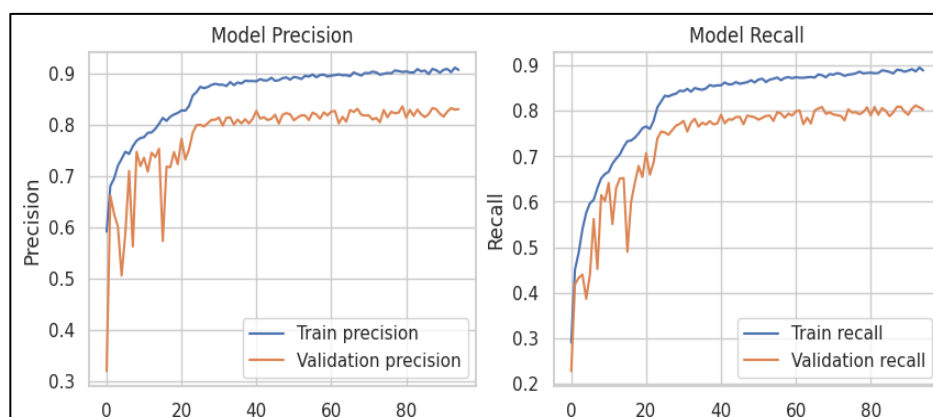


Figure 5. Precision and Recall Curves of the Proposed Work

The classification report and confusion matrix of the proposed classifier are shown in Figures 6 and 7, respectively. Here, ulcers have the highest recall, F1 score and precision compared to other dental disorders. Dental calculus has the lowest values of precision, F1 score, and recall.

Classification Report (with TTA):

	precision	recall	f1-score	support
Calculus	0.7462	0.7462	0.7462	130
Caries	0.9753	0.9916	0.9834	239
Gingivitis	0.8722	0.8462	0.8590	234
Hypodontia	0.9167	0.9429	0.9296	35
Tooth Discoloration	0.9677	0.9783	0.9730	184
Ulcers	0.9882	0.9882	0.9882	255
accuracy			0.9257	1077
macro avg	0.9111	0.9155	0.9132	1077
weighted avg	0.9251	0.9257	0.9253	1077

Figure 6. Classification Report of the Proposed Classifier

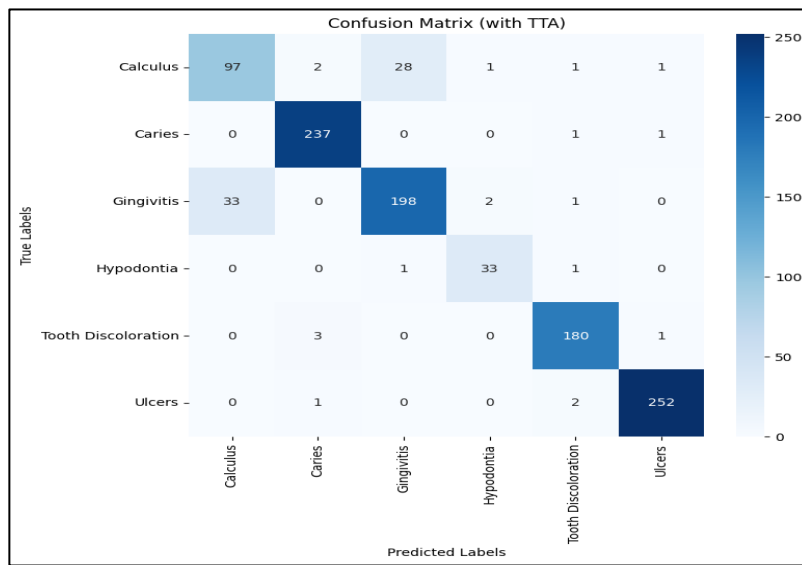


Figure 7. Confusion Matrix of the Proposed Classifier

Performance analysis of ResNext compared to conventional classification algorithms is portrayed in Table 2. The graphical representation of the comparative analysis of ResNext over other models is shown in Figure 8. The performance of the ResNext Transform model is compared to several cutting-edge models. It produces a 6.7% increase in accuracy compared to ResNet50 and a 5% increase in accuracy compared to Densenet. When compared to the ResNext model without the Transformer blocks, the precision increases by 1.8%. The model outperforms the EfficientNet model by 3.6% and the ResNext model by 1.2% in identifying real cases of illness. ResNext has specificity closer to ResNext and produces 5.4% better results than ResNet50.

Table 2. Comparative Analysis of Various Classification Algorithms

Model	Accuracy	Sensitivity	Precision	AUC	Specificity	F1-Score
Resnet50 [30]	89.12± 1.2	89.7 ± 1.5	90.1 ± 1.3	89.3 ± 1.0	90.1 ± 1.1	89.7 ± 1.4
Densenet [31]	90.9 ± 1.0	89.4 ± 1.3	91 ± 1.1	91.3 ± 0.8	90.8 ± 0.9	90.4 ± 1.2
EfficientNet [32]	91.4 ± 0.9	91.7 ± 1.1	91.8 ± 1.0	91.8 ± 0.7	91.6 ± 0.8	91.3 ± 1.0
ResNext [33]	93.6 ± 0.8	94.2 ± 1.0	93.9 ± 0.9	94.7 ± 0.6	95.2 ± 0.7	94.9 ± 0.9
Vision Transformer [34]	94.5 ± 0.6	94.9 ± 0.8	94.3 ± 0.7	94.1 ± 0.5	94.2 ± 0.6	93.9 ± 0.8
Proposed (ResNextTransform)	95.9 ± 0.4	95.4 ± 0.7	95.7 ± 0.5	95.2 ± 0.4	95.5 ± 0.5	95.1 ± 0.6

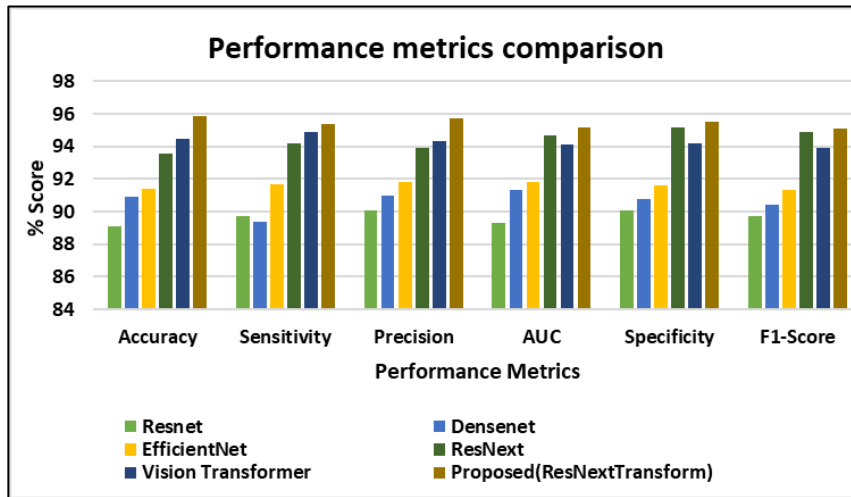


Figure 8. Performance Metrics Comparison of Classification Algorithms

CPO optimized ResNext performance with other conventional algorithms is displayed in Table 3, and the graphical representation is portrayed in Figure 9. Metaheuristic CPO optimization is applied in this work to optimize the parameters of hybrid ResNextTransform. Conventional PCO, ACO, GWO and WOA algorithms are taken for comparison with the CPO algorithm. High consistency is shown by the CPO over several random initializations. In our experiments, we repeated the optimization 5 times with different initial seeds. Despite stochastic initialization, CPO consistently converges to comparably high-quality solutions, as demonstrated by the corresponding model and the optimized hyperparameters that resulted.

The accuracy of CPO is drastically improved by the PSO algorithm by 4.6% when combined with the proposed classifier. It produces a 1% increase in the sensitivity compared with WOA. There is a minimal difference in the specificity compared to the WOA algorithm. Compared to ACO, the CPO optimized classifier has a 3.5% higher precision in properly identifying positive cases. There is a misclassification, with 28 calculus cases misclassified as gingivitis and 33 gingivitis cases wrongly classified as calculus. Fine-grained differentiation is difficult due to their similar visual characteristics, and there is co-occurrence at the borders of gingivitis.

Table 3. Comparative Analysis of the Proposed Optimized Classifier Over Other Optimization Techniques

Model	Accuracy	Sensitivity	Precision	AUC	Specificity	F1-Score
ResNextTransform+PSO [24]	92.7 ± 1.3	92.8 ± 1.2	93 ± 1.1	92.7 ± 0.9	92.5 ± 0.8	92.6 ± 0.7
ResNextTransform+ACO [25]	93.5 ± 1.1	93.9 ± 1.0	93.7 ± 1.0	94.1	93.6	93.9
ResNextTransform+GWO [26]	94.2 ± 0.9	94.6 ± 0.8	95.1 ± 0.9	94.3	95.2	94.7
ResNextTransform+WOA [35]	95.2 ± 0.8	96.4 ± 0.6	96.7 ± 0.7	97.2	96.5	96.1
ResNextTransform+CPO (Proposed)	97.3 ± 0.7	97.4 ± 0.7	97.2 ± 0.6	97.2	96.9	97.1

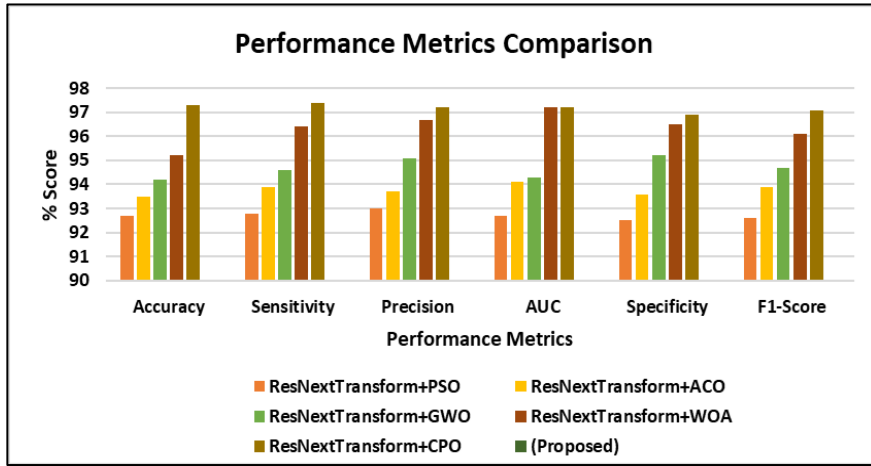


Figure 9. Performance Metrics Comparison of Optimized Classification Algorithms

The performance of the proposed classifier with and without CPO optimization is shown in Table 4, and the graphical results are displayed in Figure 10. We repeatedly test CPO with random tests, then the mean fitness and its corresponding standard deviation are reported at each iteration, which makes it easier to evaluate the robustness and convergence behavior of the suggested approach, as shown in Figure 11.

Table 4. Performance Metrics Comparison with and Without Optimization

	Accuracy	Sensitivity	Precision	AUC	Specificity	F1-Score
ResNextTransform	95.9	95.4	95.7	95.2	95.5	95.1
ResNextTransform (with CPO Optimization)	97.3	97.4	97.2	97.2	96.9	97.1

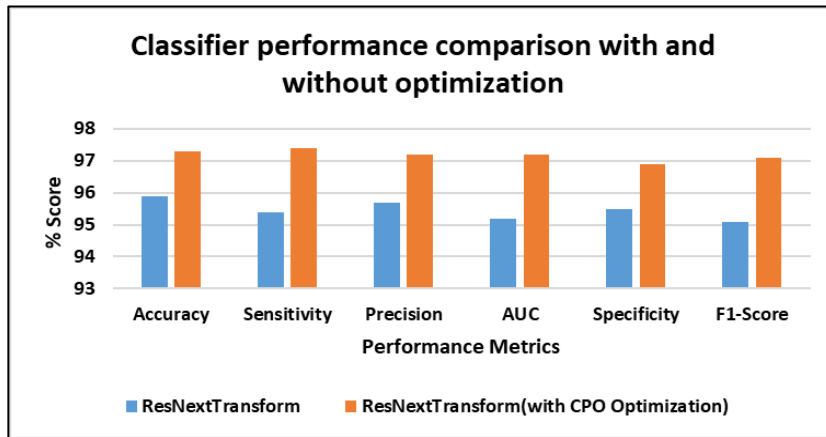


Figure 10. Classifier Performance with and Without Optimization

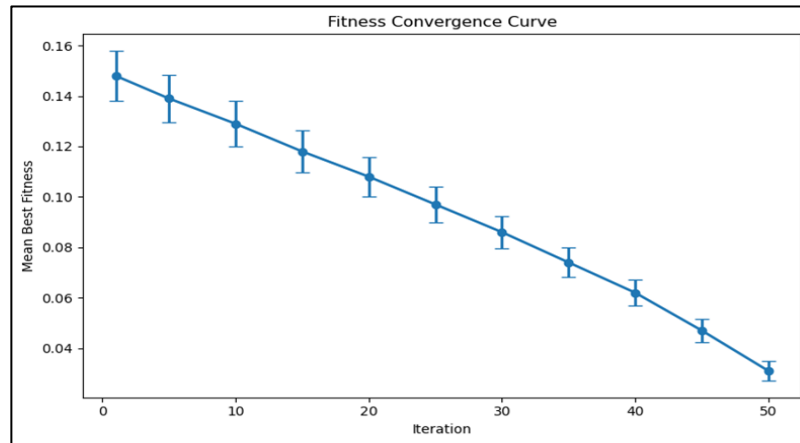


Figure 11. CPO Optimization Curve (Best Fitness vs Iterations)

5. Conclusion

The proposed work reveals that the suggested model provides a powerful and reliable strategy to accurately classify a wide range of dental disorders. In this work, a deep learning-based hybrid ResNextTransform classifier is developed to classify various kinds of oral disorders. ResNext efficiently captures fine-grained anatomical variations, intricate textures, and subtle edges, which are crucial in identifying early lesions in colored dental images for classifying various disorders. Transformers focus on the global context by patching the entire image together, unlike CNN-based models. The attention-based mechanism in the transformer is responsible for focusing on important features by discarding non-essential features and reducing time. They can easily handle a cluttered background in the case of medical images. CPO optimization is utilized to optimize the parameters of the ResNextTransform model and improve the overall accuracy of the model. Overall, the experimental results demonstrate that the performance of the proposed classifier is superior to other cutting-edge techniques and empowers the early detection of various dental disorders. This work can be further extended by concentrating on federated learning by including images from various dental clinics. Reconstruction of missing information in the images can also be generated to avoid the loss of spatial information. Dental radiographs can be combined with clinical notes to ensure an accurate diagnosis of dental disorders.

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