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Diagnosing Gingiva Disease Using Artificial Intelligence Techniques

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ABSTRACT

Gingival and periodontal diseases, such as gingivitis and periodontitis, are critical public health concerns that can lead to severe complications if left untreated. Early and precise diagnosis is crucial to mitigate the progression of these conditions and improve oral health outcomes. This study investigates the application of convolutional neural networks (CNNs) in diagnosing gingival diseases using medical images, including X-rays and intraoral photographs. Several CNN architectures, including VGG16, Sequential CNN, MobileNet, InceptionV3, and suggestions for a voting method to enhance the prediction, were evaluated for their performance in classifying gingival conditions. MobileNet emerged as the most effective model, achieving a test accuracy of 92.73%; the suggested method relies mainly on its positive result. When the MobileNet's result is false, the process takes the voting result using the other methods. This boosts the accuracy to 96%. Surpassing other models in precision and recall metrics. Pre-processing techniques such as normalization using the CIELAB color space and data augmentation significantly enhanced model accuracy. The study employed robust evaluation methods, including 10-fold cross-validation and hyperparameter tuning, to ensure model reliability and generalizability. The findings highlight the transformative potential of AI-powered diagnostic tools in dental healthcare. By leveraging lightweight and efficient architectures like MobileNet, these tools can be deployed in resource-limited settings, offering real-time diagnostic support to healthcare professionals. Future work will focus on expanding datasets, exploring ensemble models, and improving interpretability to further enhance diagnostic accuracy and clinical applicability. This research demonstrates that CNN-based models can significantly improve the early detection and management of gingival diseases, contributing to better oral health and advancing the integration of AI in medical diagnostics.

1. Introduction

Gingivitis is an inflammation of the gums or the lining tissues inside the mouth. It is usually the result of the accumulation of bacteria, plaque, tartar, mucus, and food between the teeth and gums. If this disease is not treated, abscesses and breaks will occur, the fibers linking the teeth to the gums will be destroyed, and the teeth will be removed.

Plaque is a soft, yellowish-white substance made from bacteria and debris. It is formed between teeth and along the gum line. Plaque must be removed by brushing and flossing, or it will harden to form tartar. Gingivitis is mainly caused by poor oral hygiene. Other factors that can contribute to gingivitis include an unbalanced diet and lifestyle. As is known, periodontal diseases are one of the essential reasons for tooth loss in adults [1].

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Gingivitis is a non-destructive disease that affects the gums. The most common cause of gingivitis is a lack of oral hygiene, which causes bacterial plaque to accumulate continuously. The color change classifies it due to the inflammation of the gum, which is generally pink because of abnormal vessel dilation. Gingivitis can be healed, but if left untreated, it can lead to periodontitis. Gingivitis, left unchecked, leads to plaque development, an accumulation of white blood cells that are there to fight infection. Periodontal disease is also known as gum disease. It can lead to stroke, heart disease, osteoporosis, diabetes, and even premature babies for sufferers. Early prevention and treatment of this disease are essential to maintain oral cavity health [2, 3].

Periodontal disease is generally associated with plaque and calculus that accumulate beneath the gum. Individuals also have difficulty cleaning their teeth due to this accumulation, which increases the chance of bacterial infections. In the prognosis of periodontal bone loss in oral diagnosis, the clinical method involves taking panoramic radiographs [4]. The panorama shows a flat and panoramic image of the upper and lower jawbone, consisting of facial bones with adjacent teeth and surrounding structures. When reading panoramas, the position of the teeth and the thickness of the upper and lower jaws are assessed. Periodontal disease is diagnosed by measuring the pocket depth [5]. The following section offers a comprehensive literature review, focusing on prior research on applying deep learning in gingiva disease. The methodology segment provides an in-depth explanation of the dataset, the CNN architecture, the training procedure, and the evaluation metrics employed in this study. The results section discusses the model's training and validation findings, including performance metrics and an analysis of the model's diagnostic accuracy. Lastly, the paper concludes by summarizing the main insights and proposing directions for future research in this fast-advancing field. The weaknesses of MobileNet were improved by incorporating a voting system with other models to enhance evaluation accuracy. The main contributions of the proposed voting-based ensemble method are as follows:

- Used a diverse dataset (2,270 images), enhancing generalization.
- Implemented data augmentation techniques to improve robustness.
- Employed a voting-based model combination, unlike previous single-model studies.
- The proposed method offers a superior diagnostic system for gingival diseases and outperformed existing models' accuracy and reliability.

The proposed method offers a superior diagnostic system for gingival diseases by implementing these enhancements.

2. Literature review

Edgardo Raphael Carillo et al., 2020, [6] developed a smartphone application in 2020 utilizing a Convolutional Neural Network (CNN) that can accurately diagnose gum diseases, particularly gingivitis, with an 83.5% classification accuracy based on the study. This demonstrates the feasibility of smartphone-based diagnosis but lacks a diverse dataset.

Ammar F. Mohammed et al., 2022, [7] used a CNN-based approach, particularly VGG16, VGG19, and Xception models, to accurately predict periodontal teeth from X-ray images with up to 95% accuracy, aiding in diagnosing gingival diseases, high accuracy for X-ray-based diagnosis but did not address real-time classification.

D T Salunke et al., 2022, [8] used Various CNN architectures like U-Net, ResNet, VGG16, and AlexNet, which have been successfully applied in dentistry for tasks such as dental disease classification, tooth segmentation, and caries detection. This showcases the versatility and effectiveness of deep learning models in dental applications. It showcased CNN's versatility but lacked a performance comparison between architectures.

H. Jayasinghe et al. 2022, [9] focused on diagnosing tooth-related diseases using Mask R-

CNN on radiology images, achieving 75%-80 % accuracy in identifying dental caries, periodontal disease, tooth type, and restoration quality. They emphasized radiology-based diagnosis but had relatively lower accuracy.

Marta Revilla-León et al., 2022 [10] introduced a review of Artificial intelligence models, including CNN, which show promise in diagnosing gingivitis and periodontal disease with accuracies ranging from 47% to 99%, provided a broad AI review but lacked direct implementation, effective for histopathology but not optimized for real-world application.

Kevin Joy Dsouza et al., 2022 [11] used Histopathology image classification to diagnose gingival diseases, which is achieved using a Hybrid ResNet-152 architecture with 92% accuracy, as discussed in the paper, effective for histopathology but not optimized for the world.

Kalita S. et al., 2023, [12] introduced A Novel Periodontal Disease Grade Classification Methodology using a Convolutional Neural Network that successfully diagnoses periodontal diseases, not specifically gingival diseases, achieving 94% accuracy with CNN models, strong periodontal disease classification, but focused less on gingival diagnosis.

Wen Li et al., 2024, [13], CNN models like ResNet and GoogLeNet effectively diagnose chronic gingivitis from oral images, aiding in efficient periodontal disease identification by healthcare professionals or self-examining, showed CNN effectiveness in oral imaging but lacked ensemble model testing.

The previous work uses various deep-learning models but does not use model combinations to predict the results.

3. Methodology

3.1 CNN in medical image analysis

Artificial Neural Networks (ANN), modeled by a computational method, have simulated the human brain to understand behavior. They use many interconnected processors to calculate, process, and store information. Deep learning has been introduced in medical image analysis, particularly in analyzing big data such as brain magnetic resonance, X-ray, and microscope images. Deep learning is a method for the decision-making process in various disease diagnoses, assisted by more complex training datasets and more complex models of hierarchical feature detectors with classifiers [14]. Convolutional Neural Networks (CNNs) have been developed using ANN and deep learning to recognize patterns in the training stage. ANNs have been applied to various fields, such as analyzing complex behaviors, fault detection, and medicine. Convolutional Neural Networks (CNNs) are a category of neural network architectures with an edge over other ANNs for processing varying stride transformations with less complexity. CNNs also efficiently handle image data to solve multiple image-based classification problems. Deep learning has evolved, leading to the design of convolutional neural network (CNN) architectures to extract image features and classify them. These lesser-known CNN architectures are used to solve image classification problems [15].

The basic concepts of CNN architecture are convolutional, pooling, fully connected layers, activation, loss, and optimization. The Convolutional Layer (CL) is prevalent in CNN architectures. It is the core of the CNN network, and a set of convolutional filters (kernels) with sizes like 3x3 or 5x5 are applied over the input data image pixels using component-wise multiplication and addition. The Pooling Layer (PL) is the second important layer used in CNNs, where the input image size is reduced. Fully connected layers and an output layer, which act as a classifier, boost the classification accuracy. Pooling the transferred feature maps using Average pooling and Max pooling methods performs the training process in a less complex manner and improves the dimension size of feature maps. Rectified Linear Units (ReLU) is an element-wise operation used to convert feature maps with non-linearity by filtering out negative values and setting the maximum value as 0. Loss, Optimization, and Activation Functions: The obtained feature maps are globally reduced to a single value for each output neuron using fully connected layers. The vector 'x' is the previous layer input given by Eq. 1[16, 17].

$$J(X, W, b) = \sum_{i=0}^{n} H(Xi) + L(W, b) \qquad (1)$$

where J(.) is the function to minimize the error between the actual output and the estimated output of the neural network, H(.) is the activation function, and L refers to the regularization errors. W and b are the parameters used in fully connected layers.

3.2 Oral image dataset

The investigation is also based on the oral pictures. The total number of data is 2270 high-resolution images. Based on the oral images, negative gum, and periodontal disease pictures were combined with negative images to document the percentage of gingivitis. According to existing survey data, the following simple four-level classification simulation is used for gingivitis. Photos of healthy tissue were used as negative control data. Considering the horizontal reflection and cosmetic flaws.

Color photos of oral lesions taken using intraoral and mobile cameras are included in the dataset. By using image analysis, possible oral cancers can be detected in these pictures. After consulting with medical professionals from several hospitals and colleges in Karnataka, India, these photos were taken. Original_data and augmented_data are the two folders that make up this dataset. Images of 1155 benign lesions and 1015 malignant lesions are included in the first folder. A sample of these images is shown in Figure 1. The photos produced by enhancing the original images are in the second folder. Flipping, rotating, and resizing are the applied augmentation procedures [18,19].

Figure 1: Samples of oral image dataset

3.2 Oral image dataset

This study also utilized relevant image preprocessing and augmentation methods for the proposed datasets. Some of these examples are carried over from transfer learning. The best cropping rectangle for surgery pattern images was identified with a developed novel Python code using image quantization. This new technique, which involves training an ICCS-Train CNN Model, was conducted with a learning rate of 0.0001 and a batch size of 32. This was validated using two different models, namely CNN-1 and CNN-2. Visual tools for the confusion matrix for classes were utilized to validate these newly developed models. This tool for the top-1 accuracy map with AI-based analysis was also used.

In the proposed classification model, the CIELAB color space was used to represent original images because the Colorado State University relational database-cover images in the CIELAB color space performed better regarding restored color-language accuracy. The data during the model-training process was normalized to make the initial weights, model-training process, and learning easier. This process helped the CNN model use the data correctly in the training process to learn the model weights precisely. This also made the ANN model more predictable to avoid cost function divergence during the training process. Further, this process made the gradients and weights predictable during model training for convergence purposes [20 - 22].

3.4 Training and Testing CNN Models

Here, the training and testing of models will be discussed using K-fold cross-validation, hyperparameter tuning with grid search, and random search methods. To compare the performance of models, the dataset containing 323 oral images was used, divided into majority and minority classes. Approaches' data are not oversampled since this is unsuitable for the best practice in AI development models. Random and grid searches are used for parameter searching to obtain the best hyperparameters for the AI model. As a result, the grid search for AE and transfer learning works well for training and testing models, while the CNN model works well using the random search method. This makes each experiment different when using an image dataset. The dataset must be split before the system is implemented to train and test the algorithms.

In this research, 10-fold cross-validation was used, with one set of 10% of the data used for training, another 10% of the data for validation, and the rest for testing. 10-fold cross-validation is widely known as the best way of evaluating the robustness of the algorithms by using ten different test subsets and ten training subsets. Each fold differs from the others, so the disease images are randomly distributed. The dataset consists of n = 2270 oral images labeled as images with disease or normal results. In general, the experimental analysis comprises 1) developing the CNN model for diagnosis, 2) quantitative measurements, 3) random search and validation, and 4) training and suspected hyperparameters or best practices for the AI system [23 - 25].

3.5. Data Splitting and Cross-Validation

The data-splitting step is essential for training and testing artificial intelligence models, especially those based on convolutional neural networks (CNNs). Data splitting is essential to obtain a very diverse collection of data for training and test processes. For training and testing CNN models, weighted random splitting was used, with an extra multiplicative factor, compared with a random shuffling process for the data split. Weighted splitting removes the high similarity of images between the training/validation and testing processes, which would generate an overestimation of testing model metrics. Here, $\beta = 0.9$ was set and was added to the ratio between healthy and disease-providing datasets to weigh the final split between these classes.

Cross-validation, a performance analysis technique, tests how well the models generalize to an independent dataset. This approach minimizes the risk of overfitting and underfitting.

The K-Fold cross-validation method was used. K-fold cross-validation starts by randomly shuffling the data. Then, the data was divided into K equal or as close as possible parts. For each part, an algorithm model is trained on the remaining K-1 parts and tested on the part. Then, the process happened exactly K times (the K-folds), with the test fold changed for each iteration. Finally, a metric, the mean, and the standard deviation of the K-folds are calculated. Here, the Stratified K-Fold method was used, where the sample portions in each class were kept the same over distinct testing folds [26, 27, 28].

3.6. Performance evaluation metrics

As discussed earlier, the objective of AI-type image analysis models is to provide a second opinion to dentists regarding oral health conditions occurring in patients' teeth and gums by diagnosing if any oral health-related abnormalities are present in the image. The reliability of such tools is most important from the viewpoint of patient safety; hence, performance evaluation of such tools must be carried out to evaluate their performance while considering the ability of such tools to identify positive patients against negative patients correctly. Foundational to this are the following distinct performance metrics for medical image analysis [29]. In this paper, the results of the four models are combined. Since the MobileNet model has the highest accuracy, its results are considered a high priority in conjunction with voting between the three other models, as described in Figure 2. The system uses the majority weighting decision rule among the three remaining models (i.e., VGG16, Sequential CNN, and InceptionV3) when the MobileNet result is false.

Due to its robust accuracy, the MobileNet model is the primary diagnostic tool in this study. If the MobileNet model yields a negative result, a majority vote among the remaining models determines the diagnosis. This approach ensures a balanced consideration of multiple analytical perspectives, enhancing the overall reliability of the diagnostic process. Figure 3 shows the general structure of the stages of the proposed system.

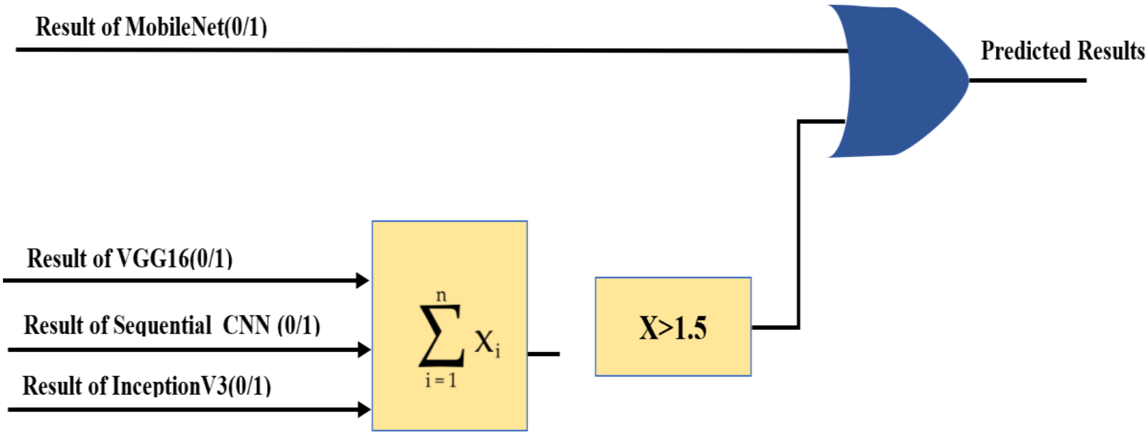


Figure 2. Scheme of new method suggested

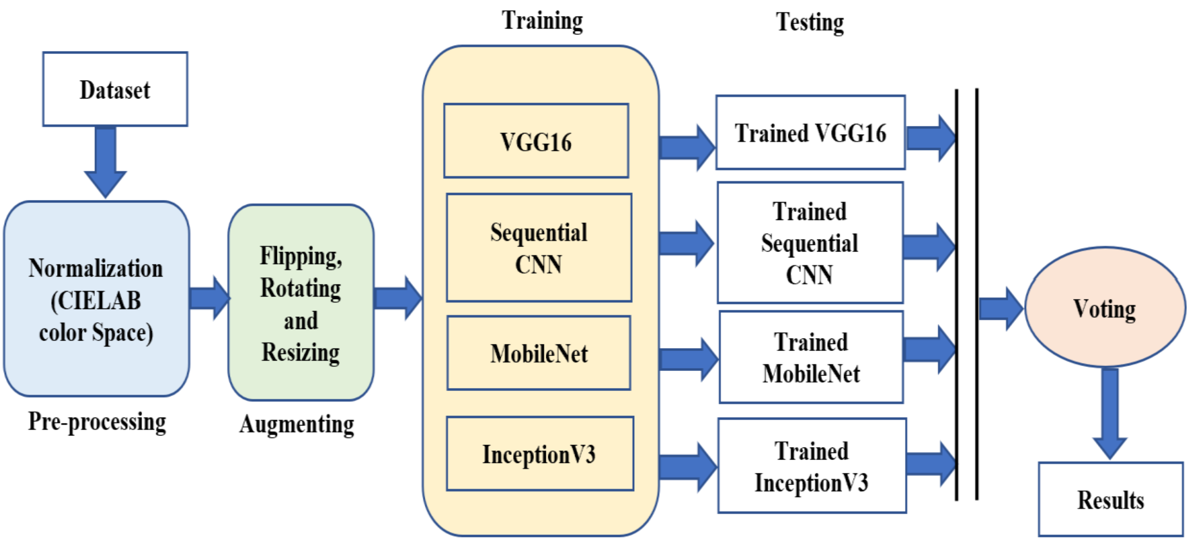


Figure 3. Proposed system general structure

Accuracy is the proportion of correct predictions against all total predicted samples. It is calculated using Eq. 1.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (1)$$

Sensitivity is the proportion of positive samples predicted as positive cases and the percentage of false negatives to the actual positive samples. It is calculated using Eq. 2.

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

Specificity is defined as the proportion of the negative samples predicted as negative cases and the percentage of false positives to the actual negative samples. It is calculated using Eq. 3:

$$Specificity = \frac{TN}{TN + FP} \quad (3)$$

F1 Score is known as a harmonic mean of precision and recall, and it can provide more accurate metrics for classes that are mistakenly classified than the accuracy measure. It is calculated using Eq. 4.

$$F1\,Score = \frac{2\,TP}{2TP + FP + FN} \quad (4)$$

4. Results

This research used four CNN deep-learning training models. The first model is VGG16, and the results in this model were:

Test Score: 0.6948
Test accuracy: 0.4758

The average training accuracy is equal to 0.5171 after epoch 100, validation accuracy is equal to 0.4758 after epoch 100, the validation loss is equal to 0.6948 after epoch 100, and the training loss is equal to 0.6929 after epoch 100 as mistakenly classified classes Figure 4a, the Confusion Matrix shown in Table 5 and Classification Report shown in Table 1.

The second model is the Sequential CNN model; the results of this model were:

Test Score: 1.4169
Test accuracy: 0.8128

After epoch 300, the average training accuracy is equal to 0.9994, the validation accuracy is equal to 0.8128, the validation loss is equal to 1.4169, and the training loss is equal to 7.716, as shown in Figure 4b, the Confusion Matrix shown in Table ٥ and the Classification Report shown in Table 2.

The Third model is the MobileNet_CNN model; the results of this model were:

Test Score: 0.6353
Test accuracy: 0.9273

The average training accuracy is equal to 0.9928 after epoch 100, validation accuracy is equal to 0.9273 after epoch 100, the validation loss is equal to 0.6353 after epoch 100, and the training loss is equal to 0.0169 after epoch 100 as in Figure 4c, the Confusion Matrix shown in Table 5 and Classification Report shown in Table 3.

The fourth model is an InceptionV3_CNN model; the results in this model were

Test Score: 0.364
Test accuracy: 0.9163

The average training accuracy is equal to 0.9642 after epoch 100, validation accuracy is equal to 0.9163 after epoch 100, the validation loss is equal to 0.3640 after epoch 100, and the training loss is equal to 0.0897 after epoch 100 as in Figure 4d, the Confusion Matrix shown in Table 5 and Classification Report shown in Table 4.

This research compared the four models to choose the best model for future CNN training. Table 9 compares 100 epochs for training and validation for VGG16, Sequential, MobileNet, and Inspection-v3 in the CNN deep-learning Model.

This paper uses a 20% validation ratio; this ratio's use in the model results in a validation accuracy of 96% for the New Method suggested,92% for MobileNet, 91% for Inspection-v3, 81% for Sequential, and 47% for VGG16.

Table 1: Classification Report of VGG16 Model

	Precision	Recall	f1-score	Support
Class 0	0.48	1.00	0.64	216
Class 1	0.00	0.00	0.00	238
accuracy			0.48	454
macro avg	0.24	0.50	0.32	454
weighted avg	0.23	0.48	0.31	454

Table 2: Classification Report Sequential CNN Model

	Precision	Recall	f1-score	Support
Class 0	0.83	0.82	0.82	240
Class 1	0.80	0.81	0.80	214
accuracy			0.81	454
macro avg	0.81	0.81	0.81	454
weighted avg	0.81	0.81	0.81	454

Table 3: Classification Report of MobileNet_CNN Mode

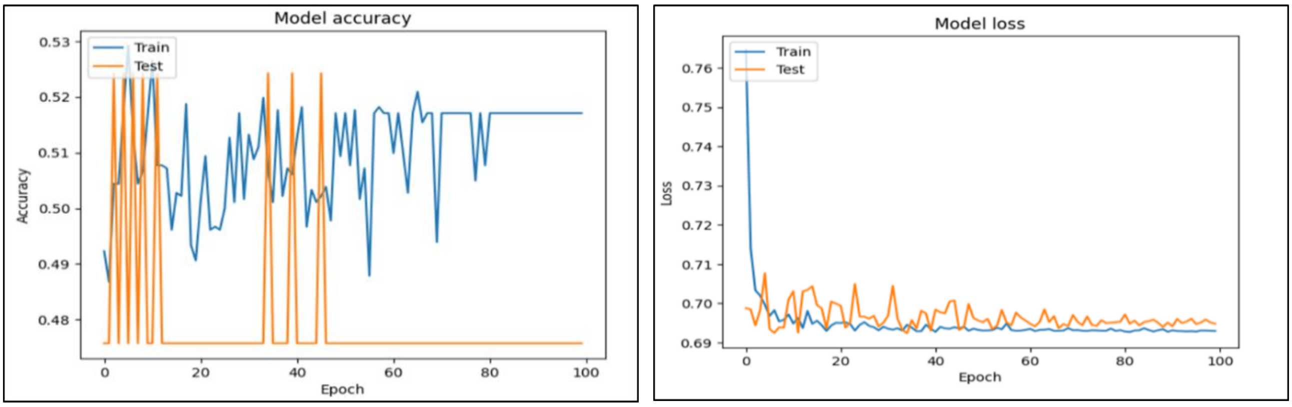
	Precision	Recall	f1-score	Support
Class 0	0.96	0.89	0.93	232
Class 1	0.90	0.96	0.93	222
accuracy			0.93	454
macro avg	0.93	0.93	0.93	454
weighted avg	0.93	0.93	0.93	454

Table 4: Classification Report InseptionV3 Model

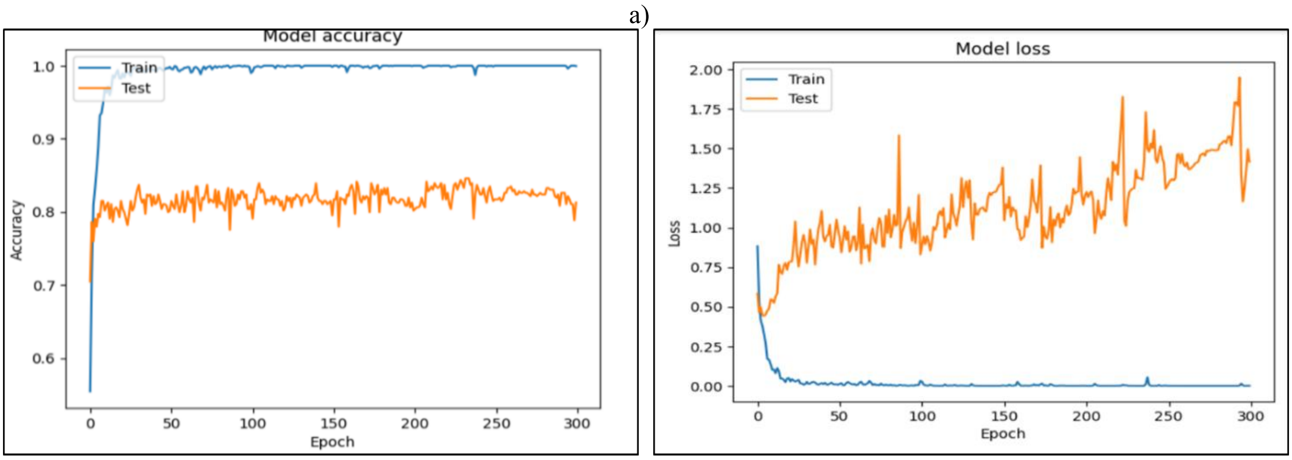
	Precision	Recall	f1-score	Support
Class 0	0.90	0.94	0.92	229
Class 1	0.94	0.89	0.91	225
accuracy			0.92	454
macro avg	0.92	0.92	0.92	454
weighted avg	0.92	0.92	0.92	454

Table 5: Comparison Table Between Four CNN Models and new method suggested

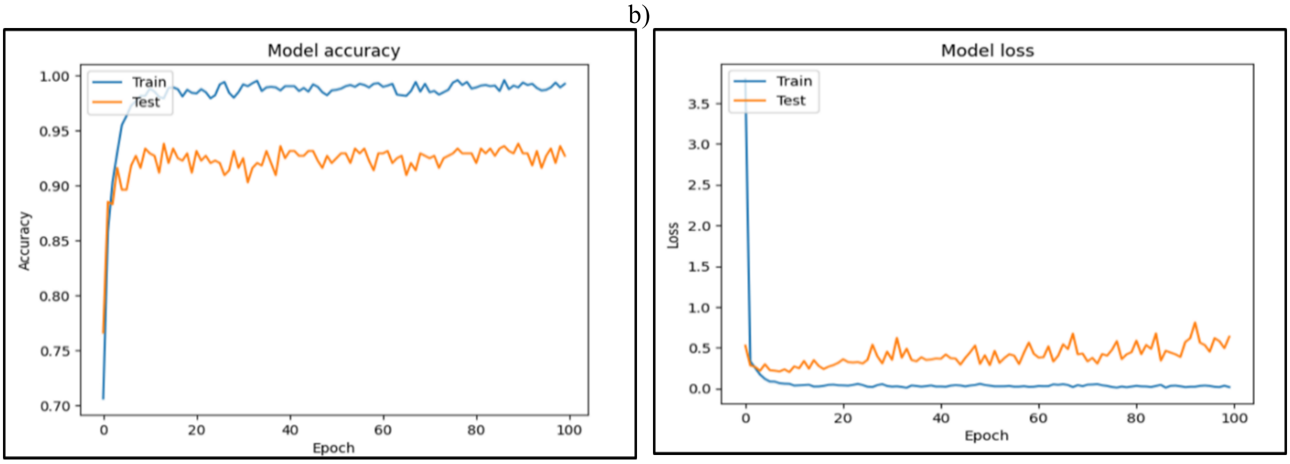
Model	validation accuracy	Actual: No Predicted: No	Actual: No Predicted: Yes	Actual: Yes Predicted: No	Actual: Yes Predicted: Yes	Accuracy of test data Rate %	Support
VGG16	0.476	216	0	238	0	47.58%	454
Sequential	0.813	196	44	41	173	81.28%	454
Inspection-v3	0.916	216	13	25	200	91.63%	454
MobileNet	0.927	207	25	8	214	92.73%	454
New Method Suggested	0.960	216	12	6	173	96%	454



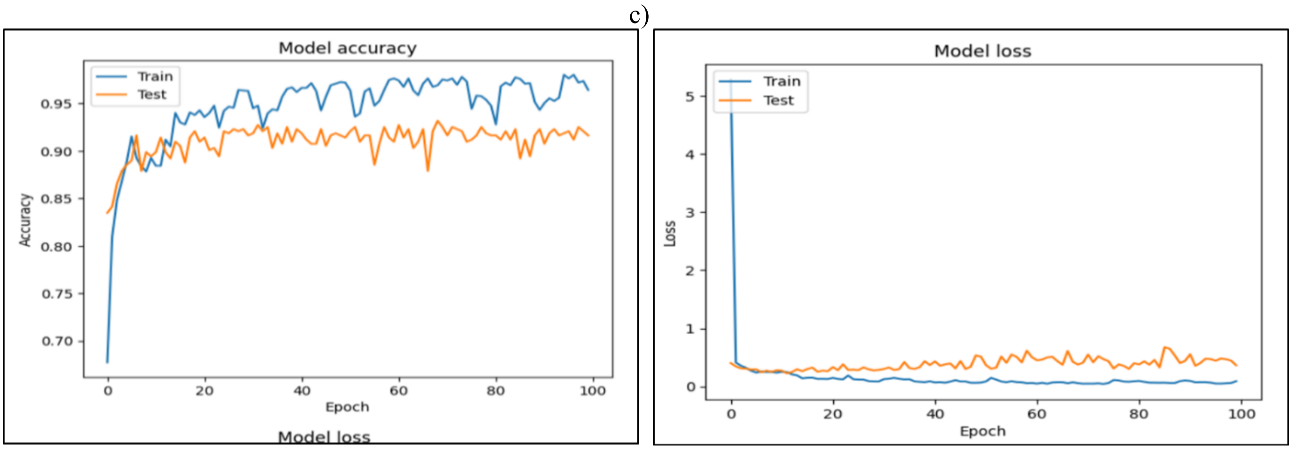
a)



b)



c)



d)

Figure 4. Accuracy and Loss for the models (a) VGG16, (b) Sequential_CNN, (c) MobileNet, and (d) InceptionV3.

Table 6: Comparison with related studies

Study	Deep Learning Techniques Used	Dataset Name & Sample Size	Accuracy/ Results
[6]	Convolutional Neural Network (CNN)	Smartphone-captured images (200 gum images)	83.5%
[7]	VGG16, VGG19, Xception	X-ray images (1,044 images)	95%
[8]	U-Net, ResNet, VGG16, AlexNet	Various dental image datasets (different sizes of images)	80%
[9]	Mask R-CNN	Radiology images (5,121 panoramic radiographs)	75%-80%
[10]	Multiple CNN architectures	Various AI-reviewed datasets (24 studies on AI models for diagnosing gingivitis and periodontal disease)	47%-99%
[11]	Hybrid ResNet-152	Histopathology images (7,900 microscopic images)	92%
[12]	CNN-based methodology	Periodontal disease dataset (1,752 bite-wing images)	94%
[13]	ResNet, GoogLeNet	Oral images dataset (3625 images)	90%
New Method Suggested	MobileNet, InceptionV3, Sequential CNN, VGG16	Oral image dataset (2,270 images)	**96%**

The proposed system was compared with closely related studies regarding accuracy, dataset name, and sample size, as shown in Table 6. The proposed method achieved 96% accuracy, surpassing previous studies like MobileNet (92.73%) and InceptionV3 (91.63%). Unlike earlier works, this method integrated multiple CNN architectures and a voting mechanism to enhance predictions.

5. Conclusion

This research explored the application of deep learning CNN for diagnosing gingival and periodontal diseases and suggested a voting method to enhance the prediction. To identify their strengths and limitations in medical image classification, the study assessed various CNN architectures, including VGG16, Sequential CNN, MobileNet, and InceptionV3. MobileNet emerged as the top-performing model with a test accuracy of 92.73%, followed by InceptionV3 at 91.63%. In contrast, the VGG16 model achieved only 47.58% accuracy, struggling due to overfitting and limited generalization capabilities. Since MobileNet's lightweight architecture demonstrated exceptional precision and recall, the suggested method relies mainly on its positive results. When the MobileNet's result is false, the process takes the voting result using the other methods. This boosts the accuracy to 96%.

The research highlighted the importance of preprocessing techniques like normalization using the CIELAB color space and advanced data augmentation methods (e.g., flipping, resizing, and rotation) in enhancing model performance. These approaches helped models effectively manage real-world dataset variations. Robust validation techniques, including 10-fold cross-validation and hyperparameter tuning through grid and random search, ensured model reliability and mitigated overfitting risks.

This study underscores the potential of MobileNet as a practical diagnostic tool for gingival diseases, especially in settings requiring lightweight and portable solutions. By providing accurate and efficient diagnostics, such AI-driven tools can support healthcare professionals as a second opinion, improving diagnostic precision and enabling early interventions. Future work could focus on expanding datasets, integrating models with clinical workflows, developing ensemble or hybrid approaches, and ensuring the model explains its ability to foster trust among healthcare providers.

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