Modified DenseNet-121 with Transfer Learning Approach for Classifying Oral Conditions

Daryl John C. Ragadio*
Technological Institute of the Philippines
Aurora Blvd., Cubao, Quezon City, Philippines
qdjcragadio@tip.ed.ph

Jonathan Taylar
AMA University
Cubao, Quezon City, Philippines
jonathan.taylar@ama.edu.ph

Ruji P. Medina
Technological Institute of the Philippines
Aurora Blvd., Cubao, Quezon City, Philippines
ruji.medina@tip.edu.ph

***Abstract*—Limited access to dental care due to expensive equipment is a challenge in developing countries like the Philippines. AI-based tools offer potential for efficient and affordable oral disease diagnosis. However, previous studies using color images have shown limitations in accuracy. This study proposes a modified DenseNet-121 deep learning model for classifying common oral diseases (calculus, cavities, gingivitis) using a limited dataset (992 images). Transfer learning was employed to adapt a pre-trained DenseNet-121 architecture. Hyper parameter tuning (kernel regularization, dropout, Adam optimizer) was implemented to enhance performance on the imbalanced dataset. The modified model achieved a remarkable 95.00% accuracy, surpassing the performance reported in prior research on small datasets for oral disease classification with an increase of 13.18%. The findings indicate that deep learning models show potential for accurately classifying oral diseases with limited datasets. To verify these findings and determine its clinical usefulness, more investigation using substantial and varied datasets is necessary.**

***Keywords*—transfer learning, densenet-121, dental conditions, cavities, calculus**

I. Introduction

Oral health is a critical component of overall well-being, and despite substantial efforts, the Philippines continues to face significant challenges such as dental caries, gum diseases, and unmet dental needs [1].

In 2018, the Department of Health indicated that dental caries impacted 92.4% of the population while 78% of Filipinos have periodontal diseases. By age six, 97.1% of children had tooth decay, and over four out of five had dentin lesions. Among twelve-year-olds, 78.4% experienced dental caries, with nearly half showing dentinogenic infections. The national DMFT index averages 8.4 for six-year-olds and 2.9 for twelve-year-olds. Additionally, 74% of the population showed signs of gingivitis, which can progress to severe periodontal disease if untreated [2].

A 2023 study in the Caraga Region found that children under nine years old are more susceptible to dental caries, while those aged 10 to 24 are more likely to experience gingivitis. Adults who are 25 years old and older are at an increased risk of developing periodontal disease [3]. The research further observed a greater occurrence of dental problems among females, as well as a significant rate of untreated dental caries in pregnant women. Furthermore, the number of orally healthy children decreased from 2017 to 2021.

These statistics underscore a critical issue: a severe shortage of dental professionals [4], with a dentist-to-patient ratio of **1: 26,608** as of 2021. The limited availability of dental services highlights the pressing necessity for creative approaches to enhance the provision of oral healthcare.

The advent of artificial intelligence (AI) and deep learning offers significant potential to tackle these challenges in an effective manner. AI-powered tools can assist with automated diagnosis of dental conditions, potentially expediting treatment and enabling earlier intervention. Deep learning algorithms can develop diagnostic tools with high accuracy, reducing the reliance on scarce dental professionals.

Research in this field is ongoing and demonstrates significant potential. For instance, a 2019 study developed a smart dental health IoT platform integrating intelligent hardware, deep learning, and mobile terminals, resulting in a significant reduction in diagnosis time and an increase in treated patients [5]. Additionally, studies have achieved an 87.11% AUC for automatic gingivitis screening [6] and 74.54% accuracy for classifying calculus and periodontal disease using customized one-dimensional convolutional neural networks [7].

However, accurately identifying dental conditions from colored images remains challenging due to the need for robust deep learning algorithms. This study explores the potential of the DenseNet-121 model, utilizing transfer learning to achieve higher classification accuracy for oral diseases such as cavities, calculus, and gingivitis.

DenseNet-121 is a powerful convolutional neural network (CNN) architecture known for its dense connections between layers [8, 9], leading to higher accuracy and efficient feature reuse [10,11]. It has been successfully applied to various image classification tasks, including weather classification [12], COVID-19 detection [13], and breast cancer detection [14]. However, its top layers produce large outputs unnecessary for classifying oral diseases, wasting computing resources and reducing efficiency. Additionally, the model's complexity can lead to overfitting, especially with small datasets, compromising reliability and generalizability [11].

To address these shortcomings, this study proposes modifications to DenseNet-121's top layers combined with transfer learning to achieve higher classification accuracy for oral diseases. The innovations include:

Global Average Pooling. Replacing traditional fully connected layers to reduce overfitting by minimizing the number of parameters.

Dense Layers. Adding dense layers with 4096 and 3072 neurons using ReLU activation function, and incorporating dropout and L2 regularization to further combat overfitting.

Output Layer. Implementing a softmax activation function to classify images into three categories: cavities, calculus, and gingivitis.

Fine-Tuning. Freezing the pre-trained layers of DenseNet-121 to retain learned features and focusing training on the newly added top layers to enhance performance for the specific classification tasks.

These modifications were specifically designed to reduce overfitting and improve computational efficiency, thereby enhancing the model's performance for the classification of oral diseases.

II. RELATED WORKS

A. *Status of Philippines on oral health care*

The Philippines faces significant challenges in maintaining good oral health among its population. The country's dental sector is heavily reliant on imported, high-quality equipment, which can make dental services inaccessible and unaffordable for many [15]. Oral diseases, such as tooth decay, discoloration, and periodontal disease, disproportionately affect population subgroups with limited economic resources and poor access to dental care [16, 17].

Oral health challenges stem from high treatment costs, limited knowledge of dental care providers, and a lack of awareness about oral hygiene's importance [18]. Additionally, the COVID-19 pandemic has further reduced preventive dental services, worsening these issues [19].

B. *Deep learning for dental classification*

AI-based dental diagnostic and treatment planning tools can enhance the efficiency and accuracy of dental care delivery. These technologies can identify high-risk populations and offer preventative care before the onset of dental issues [20]. Technologies driven by artificial intelligence have the potential to offer immediate guidance and feedback to students, thereby enhancing the learning process and elevating the standards of dental education. [21, 22].

Web-based platforms and tele-dentistry can increase access to dental services in underserved and rural communities by connecting patients with dental professionals remotely [23]. These technologies can also be leveraged to raise public awareness about oral health and promote preventive care through educational campaigns and interactive tools [24].

Deep learning, a subset of AI, can be used to train computer algorithms to identify patterns in dental data and make accurate predictions or decisions, further enhancing the capabilities of AI-based dental systems [25]. This can lead to more personalized and effective dental care, ultimately improving the overall quality of the country's dental infrastructure and workforce [26].

Nevertheless, the existing literature highlights the constraints and difficulties associated with the deployment of these technologies, including the necessity for strong algorithms, adequate data and infrastructure, as well as careful consideration of ethical and regulatory issues [27].

In 2023, Garg et al. [28] studied ResNet variants achieving over 80% classification accuracy for dental calculus and inflammation using colored images. However, ResNet variants' significant computational demands for training and inference pose a challenge, potentially limiting its deployment in real-world settings with limited resources. They also delved a lightweight architecture like MobileNetV3-Small which offer a compelling alternative. While sacrificing some accuracy around 72%, the network excels in terms of computational efficiency, making it ideal for mobile or embedded devices.

Similarly, Park et al. [7] developed a custom-designed CNNs to classify dental calculus and inflammation using colored images. The result of their study present a promising avenue for achieving good performance averaging a 74% classification accuracy while catering to resource constraints, a crucial factor for researchers exploring resource-limited environments.

Moreover, the studies exploring pixel-level segmentation tasks, like plaque segmentation, showcased the effectiveness of architectures like Supervised Pixel Based CNN at 86.42% classification accuracy [29] and DeepLabV3 at 72% result on mean intersection under union [30]. Also, in a 2021 study by Li et al. [6], a convolutional neural network (CNN) utilizing Multi-Task Learning achieved promising results for identifying gingivitis, calculus, and deposits from oral photographs. The model achieved an Area Under the Curve (AUC) of 87.11% for gingivitis, 80.11% for calculus, and 78.57% for deposits.

However, it is important to note that these architectures might require further tailoring for different segmentation objectives. This highlights the need for further research on task-specific adaptations, a key area for researchers to explore.

C. *DenseNet-121 for dental image classification*

DenseNet-121 model has demonstrated significant advantages in various image classification tasks. The model's denser connections facilitate a dense connectivity structure, wherein each layer is directly linked to all other layers in a feed-forward manner. This helps in better gradient flow across the network [31].

According to Zhou et al., [32] the dense connectivity in DenseNet-121 enables efficient feature reuse, where features learned by earlier layers are leveraged by subsequent layers. This leads to a more streamlined model characterized by a reduced number of parameters, all the while preserving superior performance levels. Additionally, DenseNet-121 has demonstrated robust transfer learning abilities, allowing pre-trained models on extensive datasets to be adapted for particular tasks. This approach minimizes the necessity of training large models from the ground up, thereby enhancing both efficiency and effectiveness. [13].

Moreover, DenseNet-121 models can be further fine-tuned and optimized for specific tasks by adjusting hyper parameters, such as learning rate, batch size, and regularization techniques.

This allows for better adaptation to the target domain and improved performance [33].

DenseNet-121's versatility extends beyond COVID-19 detection. This deep learning model has been successfully applied to various image classification tasks, including health care, weather prediction and even agricultural applications, demonstrating its robust performance across diverse domains.

Bathele et al. [34] used a transfer learning technique with a DenseNet-121 model to detect COVID-19 in both CT scans and chest X-rays. Their model achieved an accuracy of 94.25% for local CT scans and 94.0% for global chest X-rays. Also, Umair et al. [35] achieved a high accuracy of 96.49% using transfer learning with a DenseNet-121 model and Grad-CAM visualization for COVID-19 detection on an indigenously collected X-ray dataset. The model also demonstrated strong precision (93.45%), F1-score (97%), and perfect recall (100%).

Furthermore, Sriporn et al. [36] proposed a method for lung lesion prediction using chest X-rays. Their approach leveraged DenseNet-121 with transfer learning, combined with a rotational technique, Nadam optimizer, and Mish activation function. The model achieved impressive performance, reaching an accuracy of 98.88%, precision of 98.83%, recall of 98.91%, and F1-measure of 98.87%.

In addition, Ali et al. [37] conducted an analysis of histopathological images pertaining to Breast Invasive Ductal Carcinoma (BIDC) by employing a DenseNet-121 model integrated with a Channel-Wise Attention mechanism. This approach achieved an accuracy of 95.60% and an F1 score of 95.75%.

Conversely, Albelwi [12] successfully identified weather conditions from images by employing DenseNet-121. In light of the scarcity of labeled data for weather classification, they integrated transfer learning with data augmentation methods. Utilizing the ImageNet dataset, these strategies enhanced the fine-tuning of pre-trained models, thereby expediting the training process and yielding improved outcomes.

In addition, Srivastava et al. [38] modified the DenseNet-121 with pre-processing technique and data augmentation for plant disease detection to address model overfitting. Using the PlantVillage Cherry dataset, DenseNet121 achieved a 99.9% accuracy, surpassing existing models.

In a similar vein, Pillai et al. [39] utilized the deep transfer learning architecture DenseNet121 for the detection and classification of plant diseases affecting pepper, potato, and tomato crops. They utilized multiple fine-tuning layers to achieve improved and refined results. Their study achieved an accuracy of 97.38%.

III. Materials and Methods

A. *Data Set*

The dataset consists of 992 dental images. It includes 110 images of calculus obtained from the research of Park et al., (2023), 216 images of cavities, and 666 images of gingivitis uploaded by Sajid S. on Kaggle (2024). All images are stored in RGB format.

B. *Machine Learning Software*

Python is the primary programming language for its ease of use and robust machine learning libraries; Google Colaboratory is chosen for its web-based Python execution and powerful hardware; TensorFlow and Keras are used for their deep learning capabilities; NumPy for array manipulation; and Matplotlib and Seaborn for data visualization.

C. *Image Classification Process*

Step 1 Data Splitting The study utilizes a 70-20-10 train-validation-test split for DenseNet-121 training on calculus, cavities, and gingivitis images. This mitigates overfitting by evaluating on a held-out training and validation set as well as assesses generalizability using a separate test set.

Step 2 Pre-processing The pre-processing stage resizes images (224x224) for DenseNet-121 and employs Keras' ImageDataGenerator for data augmentation. Augmentation techniques (rotations, shifts, shears, zooms, flips, brightness, channel shift) with defined ranges are applied to enrich the dataset and improve model robustness.

Step 3 Validation The validation stage monitors for overfitting by comparing training and validation accuracy. It employs previously unobserved validation data to evaluate the model's capacity to generalize beyond the instances encountered during training.

Step 4 Testing The testing phase serves as the final evaluation of the modified DenseNet-121 model on completely unseen testing data. This provides a strong measure of model's generalizability and real-world performance in classifying new dental images. The complete workflow is detailed in figure 1.

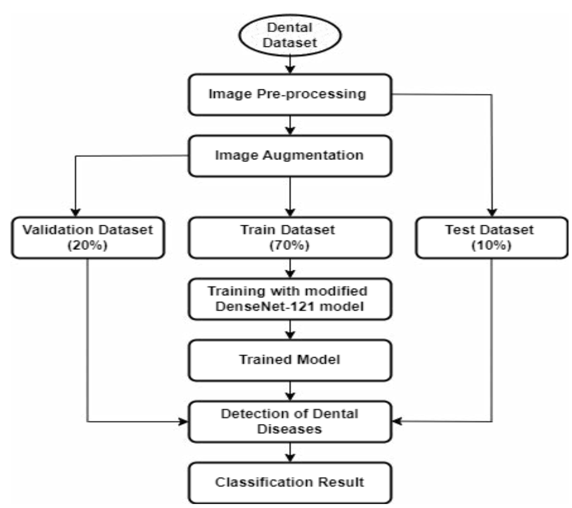

Fig. 1. Conceptual framework of the study

D. *DenseNet-121 adaptation for classification*

The top pre-trained layers of DenseNet-121 were removed and a new Softmax classifier with two dense ReLU layers (4096, 3072 neurons) is added for class probability prediction. Also, a L2 regularization with weight penalty of (0.004) and dropout (0.4) applied to dense layers to prevent overfitting. Moreover, a

Learning rate (0.001, adjusted), epochs (40), and batch size (16) optimized for training efficiency and performance.

E. Evaluation Metrics

To assess the performance of the modified DenseNet-121 model, various efficiency metrics were used with the calculations outlined accordingly.

Accuracy is defined as the ratio of correct predictions produced by the model to the overall number of predictions made.

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

Precision is the ratio of true positive predictions to the total number of positive predictions (true positives plus false positives).

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) \quad (2)$$

Recall measures the ratio of true positive predictions to the total actual positives, including true positives and false negatives.

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN}) \quad (3)$$

The F1 score harmonizes precision and recall, serving as their harmonic mean for a unified performance measure.

$$\text{F1 Score} = \frac{\text{2x Precision x Recall}}{\text{Precision+ Recall}} \quad (4)$$

Macro AUC is used in multi-class classification to represent the average area under the receiver operating characteristic curve (AUC) for each class.

$$\text{Macro\_AUC} = (1 / C) * \Sigma\ (\text{AUC\_i})\ (\text{for } i = 1 \text{ to } C) \quad (5)$$

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The modified DenseNet-121 model notably achieves superb performance as listed in Table 1. A high accuracy of 95%, demonstrating its ability to correctly classify most samples. Additionally, its outstanding precision of 96% indicates a low rate of false positives, while the decent recall of 93% suggests it effectively identifies true positives. The balanced F1 score (94%) and the elevated AUC (98.82%) further solidify its well-rounded performance and ability to distinguish between imbalance classes.

Table 1. Performance results of modified DenseNet-121 model

Metrics	Result
Accuracy	95.00
Precision	96.00
Recall	93.00
F1 Score	94.00
AUC	98.82

The modified model excelled at classifying Calculus, as shown in Table 2 (precision: 100, recall: 0.97, F1-score: 0.99). This performance indicates that the model is well-suited for oral disease classification, particularly for Calculus and Gingivitis.

Table 2. Performance result of modified model on each class

Oral Disease	Precision	Recall	F1-Score
Calculus	100	97.00	99.00
Cavities	92.00	84.00	88.00
Gingivitis	95.00	98.00	96.00

The modified model over 40 epochs has a noticeable upward trend in both training and validation accuracy as discloses in figure 2, indicating effective learning on the training data.

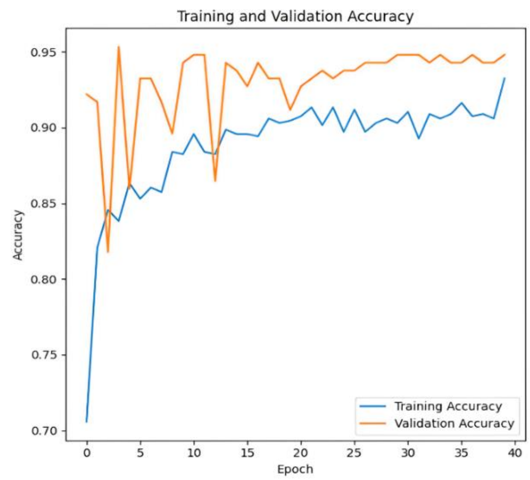

Fig. 2. Graph of Training/Validation Accuracy

Meanwhile, the training and validation loss curve demonstrates a low and stable error rate. This highlights that the network is learning at a reasonable rate during the training process. By the end of the 40 iterations, the accuracy rate shows improvement, accompanied by a decrease in the loss value, confirming successful model generalization and convergence.

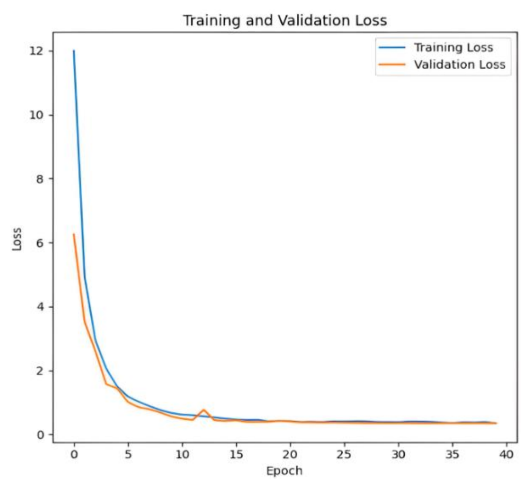

Fig. 3. Graph of Training/Validation Loss

The result from the examination of the confusion matrix in Figure 4 reveals a representation of accurate and mistaken image classifications across classes. Calculus appeared with a noteworthy 3 misclassifications, while Gingivitis followed with 15 inaccuracies. This comprehensive outcome seamlessly integrates into the computation of the DenseNet-121 model's high accuracy, elevating the significance of its overall performance.

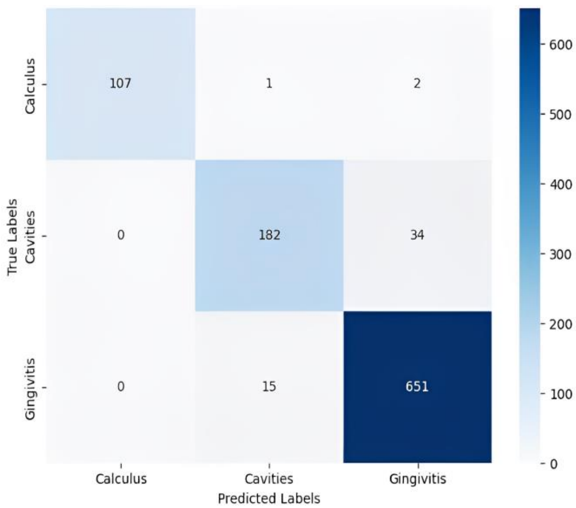

Fig. 4. Confusion Matrix

The modified DenseNet-121 model shown in Table 3 significantly outperformed earlier studies that utilized transfer learning and other CNN models for oral diseases classification. These studies employed either feature selection or customization approach in CNN, but the presented model demonstrated a notably superior performance with an increase of 13.18% classification accuracy compared to the study of Garg et al., which also leverages transfer learning technique and ResNet 34 model.

Table 3. Performance Comparison of Oral Disease Classification using CNN Models in previous studies

Study	Year	Method	Target Disease	Accuracy
Kats et al.,	2018	Faster R-CNN	Plaque	83.00 %
Liu et al.,	2019	Mask R-CNN	decayed tooth, dental plaque, uorosis, and periodontal disease	90.00 %
Li et al.,	2020	Super Pixel CNN	Plaque	86.42 %
Garg et al.,	2023	Transfer learning + ResNet 34	Calculus and Inflammation	81.82 %
Garg et al.,	2023	Transfer learning + MobileNetV3-Small	Calculus and Inflammation	72.73 %
Park et al.,	2023	Customized Parallel 1D CNN	Calculus and Inflammation	74.54 %
This study	**2024**	**DenseNet-121**	**Calculus, Cavities, Gingivitis**	**95.00 %**

V. CONCLUSIONS

This study investigated the potential of a modified DenseNet-121 architecture for classifying common oral diseases (calculus, cavities, gingivitis) using a limited dataset. The Philippines, similar to numerous developing nations, encounters difficulties in accessing oral healthcare primarily due to its dependence on costly equipment. AI-based tools offer promise for improving efficiency and affordability, however prior research on oral disease classification with color images has shown limitations in accuracy.

Our proposed approach utilizes transfer learning, adapting a pre-trained DenseNet-121 model for our specific task. This modification, along with strategic hyper parameter tuning (kernel regularization, dropout, Adam optimizer), resulted in a model achieving a remarkable 95.00% accuracy on a dataset of 992 images. This surpasses the performance reported in previous studies on small, imbalanced datasets for oral disease classification.

These findings suggest that a well-designed deep learning model can achieve high accuracy for oral disease classification even with limited data resources. Further research is needed to validate these results on larger, more diverse datasets and explore the generalizability of the model in real-world clinical settings. Additionally, future studies could investigate the model's ability to classify more complex oral pathologies.

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