MouthCare: AI Powered Mobile Application for Oral Disease Classification using an Optimized DenseNet-121 model

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Abstract—**Access to dental care in the Philippines is limited due to high and inconsistent costs, creating a need for affordable solutions. This study presents "MouthCare," an AI-powered mobile app for detecting cavities, calculus, and gingivitis using an optimized DenseNet-121 deep learning model. Through transfer learning, fine-tuning, and TensorFlow Lite, the model is efficiently deployed on mobile devices, overcoming challenges of overfitting and computational constraints. It achieved a 99.50% accuracy, a 99.97% AUC, and a 3.40-second latency, demonstrating its potential for real-time use. The model's implementation on Android devices offers a scalable approach to improving oral healthcare accessibility in the Philippines. Future work should expand the dataset to include more oral diseases, improving the model's generalizability and clinical impact.**

Keywords—Mobile Application, optimization, transfer learning, fine-tuning, densenet-121 model

I. INTRODUCTION

In 2023, approximately 22.4% of Filipinos, equating to around 25.24 million individuals, lived below the poverty line, with a family of five needing a minimum monthly income of PhP13,797 to meet basic needs. Compounding this economic hardship is the widespread prevalence of oral health issues, which affect about 87% of the population. Tooth decay and gum diseases are rampant, and eight out of ten Filipino children suffer from childhood caries. The Department of Health has identified dental caries as a "silent epidemic," impacting up to 73 million Filipinos [1][2].

Despite the severity of this public health crisis, access to dental care remains limited, largely due to the prohibitive costs and uneven distribution of dental services across different regions in the Philippines. This lack of access underscores the need for more affordable and scalable solutions to improve oral health and overall quality of life.

At the same time, the Philippines has seen a dramatic rise in digital connectivity. By 2024, there were approximately 86.75 million active social media accounts and 69 million Filipinos with internet access, making online platforms increasingly integral to daily life [3][4]. The COVID-19 pandemic further accelerated the adoption of telehealth services and mobile health applications, enabling remote access to healthcare and goods [5]. These trends suggest a growing opportunity for leveraging mobile technologies to address pressing healthcare challenges, such as oral health care, in resource-constrained settings.

Recent advances in artificial intelligence (AI), particularly deep neural networks, have transformed medical diagnostics, offering new possibilities for disease detection and classification. AI-based models have demonstrated strong performance in detecting conditions such as breast cancer, brain tumors, and glaucoma [6][7][8]. However, the application of AI to oral health—specifically through widely accessible technologies like mobile phone cameras—remains underexplored [9]. Most existing diagnostic tools rely on clinical imaging techniques such as X-rays, which are not feasible for widespread use in non-clinical settings.

DenseNet-121, a deep learning model known for its efficient use of parameters and feature reuse, has shown promise in various medical imaging tasks [10][11]. However, its computational complexity poses challenges for deployment on resource-constrained devices like smartphones [12]. To address these limitations, there is a need to adapt this architecture for efficient, real-time use in mobile health applications, specifically for oral disease detection.

In contrast to existing models that rely on clinical imaging tools such as X-rays, the proposed AI model is uniquely adapted for real-time detection of oral diseases using smartphone cameras. By optimizing DenseNet-121 with TensorFlow Lite and employing transfer learning techniques, this study contributes a highly scalable, resource-efficient solution suitable for deployment on mobile devices. This allows the model to function effectively even on lower-spec devices, making it accessible to a broader population in resource-constrained environments, such as rural areas in the Philippines.

II. RELATED WORKS

A. AI and Mobile Health Adoption in the Philippines

The rapid increase in digital connectivity in the Philippines has fostered the adoption of mobile and online applications for various services, including healthcare. By early 2024, mobile wallets like GCash and Maya had achieved 94% adoption among Filipinos, demonstrating a growing trust in digital financial services [13]. This trend reflects a broader shift towards mobile solutions in daily life, accelerated by the COVID-19 pandemic, which saw millions of Filipinos transition to online banking, e-commerce, and telemedicine services [14].

Telemedicine, in particular, experienced a surge in adoption during the pandemic, with both private and public sectors working to integrate digital health solutions into the healthcare system. Legislative measures, such as the proposed E-Health and Telemedicine Development Act, aim to create a supportive framework for expanding digital healthcare services to underserved communities [15][16]. These developments highlight the increasing reliance on mobile platforms for healthcare delivery, paving the way for innovations like MouthCare, which capitalizes on this digital infrastructure to address oral health challenges.

B. *AI for Dental Imaging and Oral Disease Detection*

Recent advancements in AI have significantly improved the automation of dental condition detection from clinical images. Chen et al. [17] utilized the YOLOv7 architecture to achieve high accuracy in tooth detection, while Al-Ghamdi et al. [18] developed a multitask convolutional neural network to classify X-ray images into dental categories with greater than 96% accuracy. Other studies, such as those by Zhang et al. [19], introduced dental radiograph datasets specifically for pediatric caries segmentation, demonstrating the efficacy of AI in complex dental diagnostics.

However, the majority of these studies rely on clinical imaging methods like X-rays, which require specialized equipment, making them impractical for regular use in non-clinical environments. For instance, Chen et al. [17] and Al-Ghamdi et al. [18] both employed X-rays in their models, limiting their applicability to clinical settings. While these models excel in controlled environments, their complexity and resource requirements restrict their accessibility for routine, widespread use, especially in developing regions where access to such technology is limited.

In contrast, research on AI models using smartphone cameras for oral disease detection is still emerging. Thanh et al. [20] evaluated a smartphone-based diagnostic tool for detecting smooth surface caries, while Birur et al. [21] validated a CNN-enabled mobile health device for frontline health workers to screen for oral lesions in low-resource settings. These studies demonstrate the potential for mobile-based AI solutions, but further refinement and optimization are necessary to make these tools more accessible, particularly in resource-constrained environments.

C. *Mobile-Based AI for Oral Health Applications*

The use of mobile phone cameras for health diagnostics has shown promise in detecting a range of diseases, but its application in oral health is still underexplored. Lin et al. [22] leveraged smartphone cameras and deep learning to detect oral cancer, significantly improving diagnostic accuracy. Shafi et al. [23] introduced an IoT-based healthcare model designed to eliminate the need for in-person visits, combining deep learning techniques with mobile applications to screen for diseases in post-COVID-19 scenarios.

In the field of dental health, Shariff et al. [24] introduced DentMA, a mobile application for caries screening using deep learning, which demonstrated strong performance in detecting various types of caries. However, these applications have yet to fully address the challenge of balancing computational demands with the limited processing power of mobile devices.

This study seeks to fill this gap by optimizing the DenseNet-121 model for mobile use, integrating transfer learning, fine-tuning and TensorFlow Lite to reduce the model's complexity while maintaining high accuracy in oral disease classification. By focusing on smartphone-based imaging, MouthCare provides an innovative solution for early detection of cavities, calculus, and gingivitis in a resource-efficient manner, bridging the gap between clinical-grade diagnostics and accessible mobile health solutions.

III. MATERIALS AND METHODS

A. *Data Set*

The dataset comprises 991 dental images categorized into 110 images of calculus, 215 images of cavities from Park et al. (2023), and 666 images of gingivitis sourced from Sajid S. on Kaggle (2024). All images are stored in RGB format.

B. *Data Splitting*

The dataset was divided into 70% training, 20% validation, and 10% testing subsets. Specifically, 695 images were used for training, 198 images for validation, and 98 images for testing. This split ensures that the model generalizes well to unseen data during testing and avoids overfitting.

The test set was withheld during the training process and was only used after the model was fully trained to evaluate its real-world performance. This ensures that no data leakage occurred between the training and testing phases.

C. *Pre-processing and Data Augmentation*

Images were resized to 224x224 pixels, with black padding added to emphasize the region of interest. The Keras ImageDataGenerator was employed for data augmentation, applying rotations, shifts, shears, zooms, flips, brightness adjustments, fill-mode, and channel shifts to enhance dataset diversity.

D. *Model Architecture and Parameters*

The DenseNet-121 architecture employed in this study consists of four dense blocks, with a total of 121 layers, including convolutional and pooling layers. The model was pre-trained on the **ImageNet** dataset, and transfer learning was applied, fine-tuning the first to fourth blocks to improve the model's performance on dental images. The original top layers were replaced with a custom architecture optimized for oral disease classification. This included a global average pooling layer, followed by two dense layers with 1026 and 512 neurons, incorporating dropout (0.3) and L2 regularization (0.003) to prevent overfitting.

The final layer was a softmax activation function for classifying input images into cavities, calculus, or gingivitis. The custom architecture reduced overfitting while improving generalizability for the mobile-based oral disease detection. The framework of the study is detailed in Fig 1.

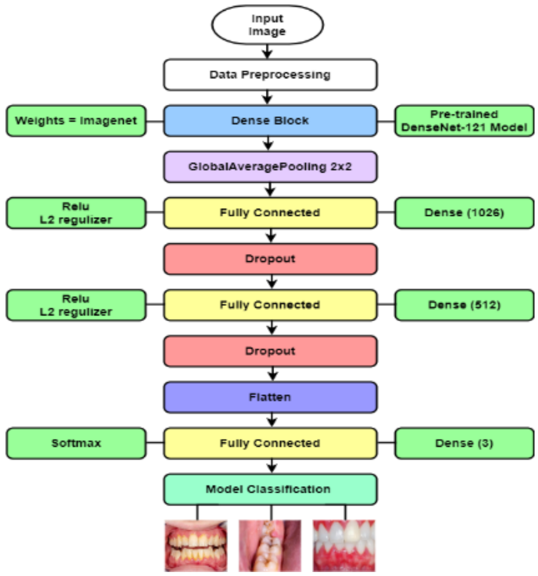

Fig. 1. Conceptual framework of the study

E. Training Parameters

Listed in Table 1 is the hyper parameters utilized to train the model.

Table 1. Model's Training Parameters

Parameters	Value
Learning Rate	0.001
Optimizer	Adam
Batch Size	16
Number of Epochs	30
Loss Function	Categorical Cross-Entropy
Dropout Rate	0.3
L2 Regularization	0.003

Early stopping, learning rate scheduler and a reduced learning rate on plateau were employed to prevent overfitting.

F. Mobile Deployment

The trained and improved DenseNet-121 model was converted to TensorFlow Lite (TFLite) for efficient deployment on mobile devices, optimized for resource-constrained environments.

G. Evaluation Metrics

The model's performance was assessed using various metrics:

Accuracy measures the ratio of correctly predicted instances to the total instances.

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

Precision shows the ratio of correctly predicted positive observations to the total predicted positives.

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

Recall measures the ratio of correctly predicted positive observations to all observation in the actual class.

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

The F1 score is the harmonic mean of precision and recall, useful for measuring the balance between them.

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

Macro AUC is the average area under the curve scores for each class, treating all classes equally. It is suitable for multi-class classification problems, especially when classes are imbalanced.

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

Latency refers to the time taken to complete a task, calculated as total operations divided by operations per second.

$$\text{Latency} = \text{total operations/operations per second} \quad (6)$$

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The optimized DenseNet-121 model demonstrated strong performance in classifying the three oral diseases including cavities, calculus, and gingivitis based on dental image. The performance evaluation of the model was carried out using multiple metrics, including accuracy, precision, recall, F1-score, AUC (Area Under the Curve), and latency, as well as an analysis of its deployment on different mobile devices.

The proposed AI model enhances traditional dental detection models by integrating transfer learning, fine-tuning and TensorFlow Lite to achieve high accuracy while reducing computational complexity for mobile use. This allows for more accurate identification of cavities, calculus, and gingivitis in a shorter processing time compared to existing AI-based dental diagnostics. Furthermore, the DenseNet-121 architecture, optimized for oral image analysis, significantly improves detection accuracy over previous approaches. For instance, while models like **ResNet34** with transfer learning reported an accuracy of **81.82%** for detecting calculus and inflammation, and **MobileNetV3-Small** achieved only **72.73%** accuracy in a similar task by Garg et al. [27], the optimized **DenseNet-121** model in this study achieves an overall accuracy of **99.50%.**

Moreover, the integration of global average pooling, dropout, and L2 regularization in the custom top layers of DenseNet-121 eliminated the overfitting while maintaining high classification performance. In comparison, Liu et al. [28], employed a **Mask R-CNN** model for dental conditions such as decayed teeth, dental plaque, fluorosis, and periodontal disease, achieving **90.00%** accuracy, which is substantially lower than the results achieved by the optimized DenseNet-121 model for cavities, calculus, and gingivitis.

Table 2 summarizes the performance of the optimized DenseNet-121 model in this study compared to other models in the literature.

Table 2. Comparison of Dental AI Models

Author(s)	Year	Model	Oral Conditions Detected	Accuracy
Liu et al.,	2019	Mask R-CNN	decayed tooth, dental plaque, uorosis, and periodontal disease	90.00 %
Garg et al.,	2023	Transfer learning + ResNet 34	Calculus and Inflammation	81.82 %
Garg et al.,	2023	Transfer learning + MobileNetV 3-Small	Calculus and Inflammation	72.73 %
This study	**2024**	**DenseNet-121 + Fine-Tuning + Transfer Learning**	**Calculus, Cavities, Gingivitis**	**99.50 %**

This improvement in accuracy can be attributed to the region of interest done in pre-processing stage and the dense connectivity within the DenseNet-121 architecture, which promotes feature reuse, allowing the model to extract more robust representations from oral images. The use of TensorFlow Lite further enhances the model's practical applicability by optimizing it for resource-constrained environments, such as mobile devices.

The performance of the DenseNet-121 model across all classes of oral diseases is presented in Table 3**.** The model achieved an overall accuracy of 99.50%**,** which far exceeds that of previous models mentioned. The precision and recall were both 99.00%**,** with an F1-score of 99.00%**.** The AUC was 99.97%**,** indicating near-perfect classification capability even in the presence of imbalanced dataset. The latency of 3.40 seconds suggests that the model is well-suited for real-time classification on mobile devices.

Table 3. Performance of optimized DenseNet-121 model

Metrics	Result
Accuracy	99. 50 %
Precision	99.00 %
Recall	99.00 %
F1 Score	99.00 %
AUC	99.97 %
Latency	3.40 seconds

The breakdown of the model's performance across the three oral disease categories—calculus, cavities, and gingivitis—is shown in Table 4**.** The model excelled in detecting gingivitis**,** achieving perfect precision, recall, and F1-score of 100%**.** For calculus and cavities**,** the model performed well with 99.00% in precision, recall, and F1-score, respectively.

Table 4. Class-Specific Performance

Oral Disease	Precision	Recall	F1-Score
Calculus	98.00%	98.00%	98.00%
Cavities	99.00%	99.00%	99.00%
Gingivitis	100%	100%	100%

The model's perfect classification of gingivitis is particularly significant, as this condition affects a large portion of the population in the Philippines. Similarly, the high classification performance for calculus and cavities suggests that the model is highly effective for diagnosing these common dental conditions.

The training and validation curves for accuracy and loss, as presented in Fig. 2 and 3, indicate a well-tuned model. The accuracy curve shows that the model achieved stable performance over time, with training and validation accuracies converging by the end of the training process.

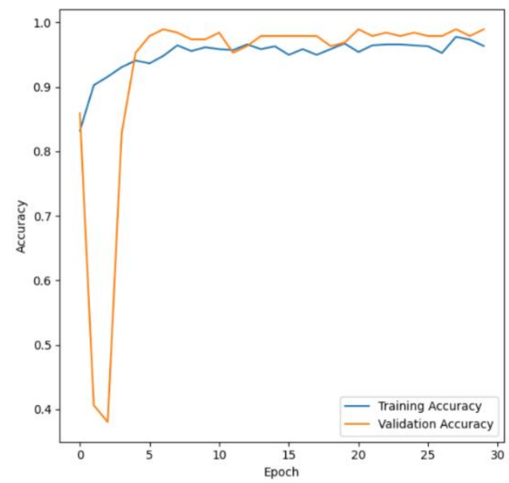

Fig. 2. Graph of Training/Validation Accuracy

The loss curves in Fig. 3 exhibit a steady reduction in both training and validation loss, further suggesting that the model is learning effectively. The convergence of the curves towards the later epochs indicates that the model is not just memorizing the training data but generalizing well to unseen data.

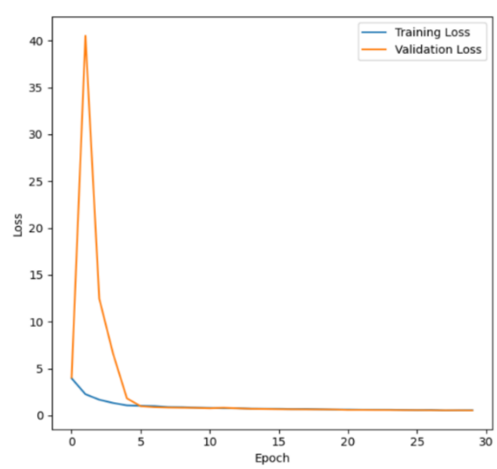

Fig. 3. Graph of Training/Validation Loss

The confusion matrix in Fig. 4 provides a visual representation of the classification results for each oral disease. Out of all test images, there was only one misclassified image for gingivitis, and two misclassified images each for cavities and calculus. This demonstrates that the DenseNet-121 model makes very few classification errors, further confirming its reliability in practical applications.

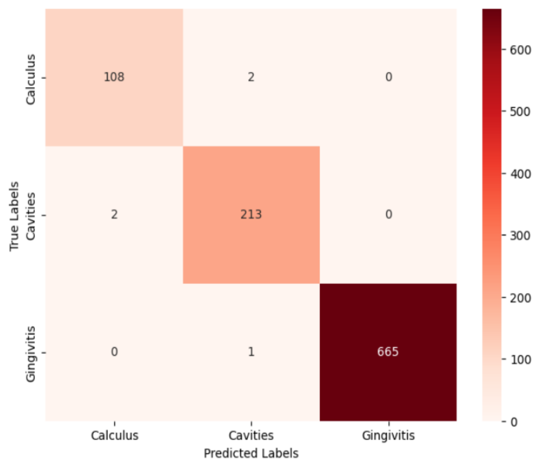

Fig. 4. Confusion Matrix

As listed in Table 5, the TensorFlow Lite-optimized DenseNet-121 model was deployed on several Android devices, demonstrating impressive classification times across varying specifications. The Infinix Zero 5G, for example, achieves a classification time of 277 ms for calculus, showcasing the potential for real-time disease detection on mobile phones.

Table 5. Performance result of the optimized model on mobile phones

Mobile Phone Specifications	Oral Diseases Classified	Accuracy	Classification Time
Infinix Zero 5G Android Version 12 11GB RAM Dimensity 900 Processor 128GB device storage 48 mega-pixel rear camera	Calculus Cavities Gingivitis	99.73% 99.95% 100%	277 ms 320 ms 285 ms
Oppo A92 Android Version 11 13GB RAM Qualcomm Snapdragon 665 Processor 128GB device storage 48 mega-pixel rear camera	Calculus Cavities Gingivitis	99.73% 99.95% 100%	1.0 second 1.0 second 1.0 second
Realme C30s Android Version 12 5GB RAM Octa-core Processor 64GB device storage 8 mega-pixel rear camera	Calculus Cavities Gingivitis	99.73% 99.95% 100%	2.0 seconds 2.0 seconds 2.0 seconds

Fig. 5 illustrates the optimized deep learning model for oral disease detection, demonstrating its seamless integration into a mobile application. This highlights its practical applicability and effectiveness in real-world scenarios, offering a portable and efficient solution for early diagnosis and management of oral health conditions.

Fig. 5. Teeth Disease Classification on Mobile Phone

V. CONCLUSIONS

Access to dental care in the Philippines remains limited due to the high and variable costs of checkups, highlighting the urgent need for cost-effective solutions to improve oral health. This study introduces 'MouthCare,' an AI-powered mobile application designed to classify common oral diseases—cavities, calculus, and gingivitis using an optimized DenseNet-121 model. By leveraging transfer learning, fine-tuning, and TensorFlow Lite, the model is adapted for efficient mobile performance, addressing overfitting and computational constraints.

The optimized DenseNet-121 model not only achieves high accuracy but also balances performance efficiency, making it a strong candidate for deployment in settings that demand reliability and precision. Its successful implementation on Android devices demonstrates the potential for widespread use in mobile health applications, offering a practical, accessible tool for early detection and intervention in oral health.

This integration of AI with mobile technology showcases the feasibility of real-time diagnostic solutions outside traditional clinical environments, significantly contributing to public health outcomes. Future research is recommended to include a larger, more diverse dataset to expand the model's diagnostic capabilities across a wider range of oral diseases.

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REFERENCES

[1] Mapa, C. D. S. (2023, December 22). Preliminary 2023 First Semester Official Poverty Statistics (Release No. 2023-391). National Statistician and Civil Registrar General, Undersecretary. Retrieved from https://www.psa.gov.ph/statistics/poverty

[2] Crisostomo, S. (2023, May 25). 73 million Pinoys suffering from tooth decay. The Philippine Star. https://www.philstar.com/nation/2023/05/25/2268760/73-million-pinoys-suffering-tooth-decay

[3] Kemp, S. (2024, February 21). Digital 2024: The Philippines. Datareportal. https://datareportal.com/reports/digital-2022-philippines

[4] Balita, C. (2024, March 4). Mobile apps with the most downloads Philippines 2023. Statista. https://www.statista.com/statistics/1363309/philippines-most-downloaded-mobile-apps/

[5] Zakerabasali, S., Ayyoubzadeh, S. M., Baniasadi, T., Yazdani, A., & Abhari, S. (2021). Mobile health technology and healthcare providers: systemic barriers to adoption. Healthcare Informatics Research, 27(4), 267-278.

[6] Potsangbam, J., & Devi, S. S. (2024). Classification of Breast Cancer Histopathological Images Using Transfer Learning with DenseNet121. Procedia Computer Science, 235, 1990-1997.

[7] Raza, A., Alshehri, M. S., Almakdi, S., Siddique, A. A., Alsulami, M., & Alhaisoni, M. (2024). Enhancing brain tumor classification with transfer learning: Leveraging DenseNet121 for accurate and efficient detection. International Journal of Imaging Systems and Technology, 34(1), e22957.

[8] Hadi, W. J., Ajrash, A. S., Salman, S. M., & Ibrahim, M. T. (2024). Densenet Model for Binary Glaucoma Classification Performance Assessment with Texture Feature. Baghdad Science Journal.

[9] Ding, B., Zhang, Z., Liang, Y., Wang, W., Hao, S., Meng, Z., ... & Lv, Y. (2021). Detection of dental caries in oral photographs taken by mobile phones based on the YOLOv3 algorithm. Annals of Translational Medicine, 9(21).

[10] Echtioui, A., & Ayed, Y. B. (2024). Automated detection of COVID-19 based on transfer learning. Multimedia Tools and Applications, 83(11), 33731-33751.

[11] Zhang, YD., Satapathy, S.C., Zhang, X. et al. COVID-19 Diagnosis via DenseNet and Optimization of Transfer Learning Setting. Cogn Comput 16, 1649–1665 (2024). https://doi.org/10.1007/s12559-020-09776-8.

[12] Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., ... & Farhan, L. (2021). Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. Journal of big Data, 8, 1-74

[13] Raon, C. J. B., De Leon, M. V., & Dui, R. (2021). Adoption of e-payment systems in the Philippines. Jurnal Ilmu Komunikasi, 18(1), 123-136.

[14] Howe, S. (2024, May 3). Social media statistics in the Philippines. Meltwater. https://www.meltwater.com/en/blog/social-media-statistics-philippines

[15] Cordero Jr, D. A. (2023). Telehealth during the COVID-19 pandemic in the Philippines. Family practice, 40(1), 207-208

[16] Aban, Y. K. C., Abunto, J. V., Aliorde, J. V. E. P., Benson, N. C. M., Figueroa, E. R. U., Masiddo, J. A. D., ... & Legatub, F. R. M. (2023). The Rise of Telemedicine in the Philippines during COVID-19: A Systematic Review of Utilization Trends and Patient Outcomes. Philippine Social Science Journal, 6(4), 9-18.

[17] Chen, I. D. S., Yang, C. M., Chen, M. J., Chen, M. C., Weng, R. M., & Yeh, C. H. (2023). Deep learning-based recognition of periodontitis and dental caries in dental x-ray images. Bioengineering, 10(8), 911.

[18] Al-Ghamdi, A. S. A. M., Ragab, M., AlGhamdi, S. A., Asseri, A. H., Mansour, R. F., & Koundal, D. (2022). Detection of Dental Diseases through X-Ray Images Using Neural Search Architecture Network. Computational Intelligence and Neuroscience, 2022(1), 3500552.

[19] Zhang, Y., Ye, F., Chen, L., Xu, F., Chen, X., Wu, H., ... & Huang, X. (2023). Children’s dental panoramic radiographs dataset for caries segmentation and dental disease detection. Scientific Data, 10(1), 380.

[20] Thanh, M. T. G., Van Toan, N., Ngoc, V. T. N., Tra, N. T., Giap, C. N., & Nguyen, D. M. (2022). Deep learning application in dental caries detection using intraoral photos taken by smartphones. Applied Sciences, 12(11), 5504

[21] Birur N, P., Song, B., Sunny, S. P., Mendonca, P., Mukhia, N., Li, S., ... & Kuriakose, M. A. (2022). Field validation of deep learning based Point-of-Care device for early detection of oral malignant and potentially malignant disorders. Scientific Reports, 12(1), 14283.

[22] Lin, H., Chen, H., Weng, L., Shao, J., & Lin, J. (2021). Automatic detection of oral cancer in smartphone-based images using deep learning for early diagnosis. Journal of Biomedical Optics, 26(8), 086007-086007.

[23] Shafi, I., Sajad, M., Fatima, A., Aray, D. G., Lipari, V., Diez, I. D. L. T., & Ashraf, I. (2023). Teeth lesion detection using deep learning and the Internet of Things post-COVID-19. Sensors, 23(15), 6837.

[24] Shariff, M., Singh SM, P., DP, S., MH, V., & Poornima, A. S. (2024). Convolutional neural network for detection of oral cavity leading to oral cancer from photographic images. International Journal of Computing and Digital Systems, 15(1), 865-877.

[25] Park, S., Erkinov, H., Hasan, M. A. M., Nam, S. H., Kim, Y. R., Shin, J., & Chang, W. D. (2023). Periodontal disease classification with color teeth images using convolutional neural networks. Electronics, 12(7), 1518.

[26] Sajid, S. (2023, October). Oral diseases dental condition dataset. Kaggle. https://www.kaggle.com/datasets/salmansajid05/oral-diseases/data

[27] Garg, A., Lu, J., & Maji, A. (2023). Towards Earlier Detection of Oral Diseases On Smartphones Using Oral and Dental RGB Images. *arXiv preprint arXiv:2308.15705*.

[28] Liu, L., Xu, J., Huan, Y., Zou, Z., Yeh, S. C., & Zheng, L. R. (2019). A smart dental health-IoT platform based on intelligent hardware, deep learning, and mobile terminal. IEEE journal of biomedical and health informatics, 24(3), 898-906.