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Web-Based Dental Caries Detection Using a Convolutional Neural Network and OpenCV

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ABSTRACT

Early detection of dental caries presents a significant challenge, particularly in regions with limited access to healthcare services. While many AI models focus on binary classification, real-world applications must handle irrelevant inputs to be robust. This study develops and evaluates a web-based system using a Convolutional Neural Network (CNN) for a three-class dental image classification task: 'Caries', 'No Caries', and 'Not a Tooth'. The method employs transfer learning with the MobileNetV3 Small architecture, trained on a custom augmented dataset of 5,811 images. The model was implemented into an accessible web application using the Flask framework and OpenCV library, supporting both image upload and real-time detection. On the test set, the model achieved an overall accuracy of 93%. It demonstrated exceptional performance in rejecting irrelevant images and high reliability in identifying caries. This study presents a practical and robust tool for initial dental screening, highlighting the importance of a dedicated 'non-target' class for building trustworthy real-world AI applications in tele-dentistry.

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1. INTRODUCTION

Dental caries, or tooth decay, is a prevalent global health issue affecting billions of people across all age groups. The condition not only leads to physical complications such as acute pain and systemic infections but also impacts psychosocial aspects, including work productivity. Early detection is crucial, yet conventional methods like visual inspection and radiography have significant limitations. Early-stage carious lesions are often microscopic or located in interdental areas, making them difficult to identify through conventional means. Furthermore, manual examination methods face challenges such as subjective interpretation among examiners, substantial resource requirements, and limited service reach in areas with poor health infrastructure. In many remote regions, access to even basic diagnostic tools is scarce, leading to caries detection often occurring only at advanced stages [1].

The advancement of Artificial Intelligence (AI), particularly the Convolutional Neural Network (CNN), offers a revolutionary solution to these challenges. CNNs have a superior ability to recognize complex patterns in medical imagery, proving more effective than conventional methods in detecting early-stage caries [2]. To support this performance, image processing using libraries like OpenCV is critical. OpenCV provides optimized algorithms for pre-processing tasks such as contrast normalization and edge detection, which are essential for preparing dental images for CNN classification, especially in resource-limited environments [3].

Previous studies substantiate this potential. For instance, CNNs have achieved up to 92% accuracy in distinguishing carious lesions from healthy tissue [4] and have reached 94.5% specificity when combined with a two-stage segmentation approach [5]. The use of transfer learning further allows models to adapt effectively to smaller, specialized datasets, which is a common challenge in medical imaging [6][7]. Even web-based implementations have demonstrated high accuracy on heterogeneous smartphone images, showing potential for self-screening in remote areas [8]. However, major challenges persist, including the model's ability to generalize across images with variations in lighting, resolution, and angle [9], and the fact that most datasets originate from specialized clinics, which may not represent the general population [10]. This research aims to address these limitations by developing a robust and accessible dental caries detection system.

Therefore, this study focuses on designing a three-class Convolutional Neural Network model to classify images as 'Caries', 'No Caries', or 'Not a Tooth' to improve diagnostic reliability and robustness. This model is implemented in a web-based application that leverages OpenCV for image processing and supports both image uploads and real-time camera detection. The primary objective is to provide an accurate, robust, and accessible initial screening solution for the general public, particularly for those in regions with limited healthcare services.

2. RESEARCH METHOD

This research was conducted through several structured stages to ensure a systematic approach. The process began with the collection and preparation of the image dataset, which included data augmentation and pre-processing to create a robust foundation for the model. Subsequently, the core of the study involved designing and training the Convolutional Neural Network (CNN) model, leveraging a transfer learning approach. The trained model was then integrated into a functional web application developed using the Prototyping methodology. Finally, the system underwent comprehensive testing, which included functional validation of the application and a quantitative performance evaluation of the model using standard classification metrics.

2.1 Dataset and Image Preparation

The study utilized a composite dataset of 5,811 images, created by combining images from a public Kaggle collection, Roboflow Universe, and a private collection of original photographs. This diverse dataset was categorized into 'Caries', 'No Caries', and 'Not a Tooth'. To improve model generalization and address class imbalance, data augmentation techniques such as horizontal flips and rotations were applied [11]. The final dataset was partitioned into training (80%), validation (10%), and testing (10%) sets, with the detailed distribution shown in Table 1. Before training, all images underwent a pre-processing pipeline using OpenCV, which included resizing to 224x224 pixels and pixel normalization.

Table 1. Dataset Distribution

Class	Training (80%)	Validation (10%)	Testing (10%)	Total
Caries	2032	254	268	2554
No Caries	1717	215	194	2126
Not a Tooth	899	112	120	1131

2.2 CNN Model Architecture and Training

This study employed a transfer learning methodology, utilizing the MobileNetV3 Small architecture [12] as a pre-trained feature extractor due to its high computational efficiency. The convolutional base of the model, pre-trained on the large-scale ImageNet dataset, was frozen to retain its powerful, generalized feature extraction capabilities. A custom classification head was then attached to this base to perform the specific task of multi-class classification 'Caries', 'No Caries', or 'Not a Tooth'. This head was designed to interpret the extracted features, beginning with a GlobalAveragePooling2D layer to reduce dimensionality, followed by two Dense layers of 128 neurons, each regularized by a Dropout layer with a 0.2 rate to prevent overfitting. The architecture is completed by a final Dense output layer which uses a softmax activation function, ideal for distributing a probability score across the three output classes.

The model was compiled for training using the Adam optimizer [13], an adaptive algorithm well-suited for computer vision tasks, with an initial learning rate of 0.001. The Categorical Cross-Entropy loss function was chosen as it is standard for measuring error in multi-class problems. The model was trained for 30 epochs with a batch size of 32, and an

Early Stopping callback was implemented to monitor validation loss and halt the training if performance ceased to improve.

2.3 Web Application Development

The trained CNN model was integrated into a user-facing system as a web application to ensure broad accessibility and ease of use. The development process followed the Prototyping methodology, an iterative approach chosen for its flexibility. This process began with a communication phase to define user requirements, followed by quick planning and modeling of the system's core functionalities. An initial prototype was then constructed and deployed for feedback, allowing for iterative refinement of the user interface and features.The web application's backend was built using Flask, a Python micro-framework selected for its lightweight nature and seamless integration with the TensorFlow/Keras model.

A key architectural decision was to load the pre-trained CNN model (as an .h5 file) into memory upon server startup. This ensures that the computationally intensive model is readily available for inference, allowing predictions to be processed with minimal latency. The user interface was developed with standard HTML, CSS, and JavaScript, focusing on a clean and intuitive design.

The system was engineered to support two primary detection workflows. For static image uploads, the user selects a file via the frontend, which is sent to a dedicated Flask endpoint. The backend then processes this image through the OpenCV pipeline before feeding it to the model and returning a results page. For the real-time feature, a separate endpoint utilizes OpenCV to capture the device's camera feed. Each frame is processed individually by the backend, and the annotated result is then streamed directly back to the user's browser, creating an interactive and continuous feedback loop

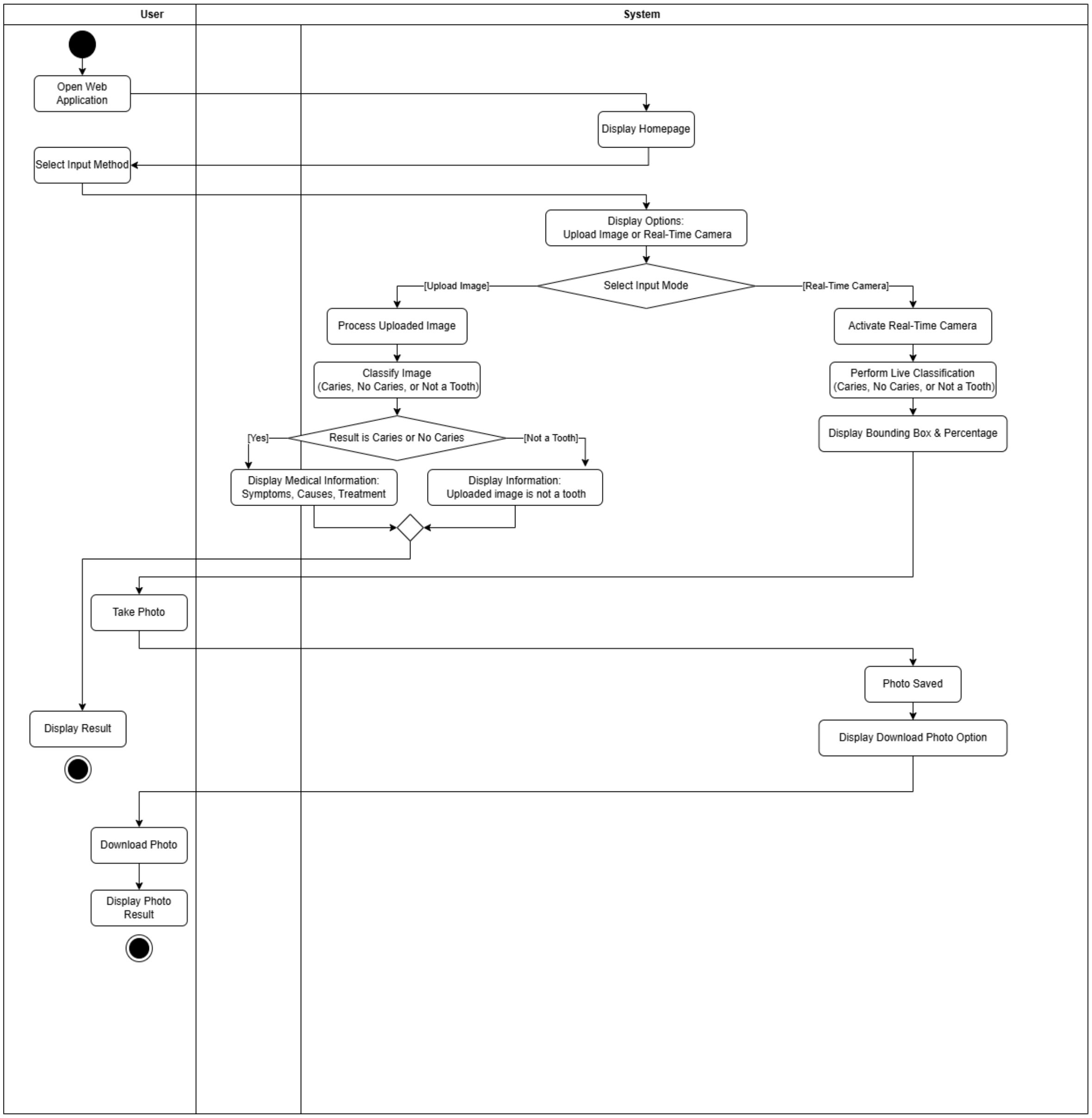


Figure 1. Web Application Workflow Diagram

2.4 System Testing and Evaluation Metrics

The system underwent a two-pronged evaluation process to validate both its functionality and performance. First, the web application's features were tested using a black-box testing approach. This method focused on verifying the external behavior of the system without considering its internal code structure. Test cases were designed to ensure that all functionalities including image upload, real-time camera streaming, and the display of prediction results worked correctly and as expected from a user's perspective.

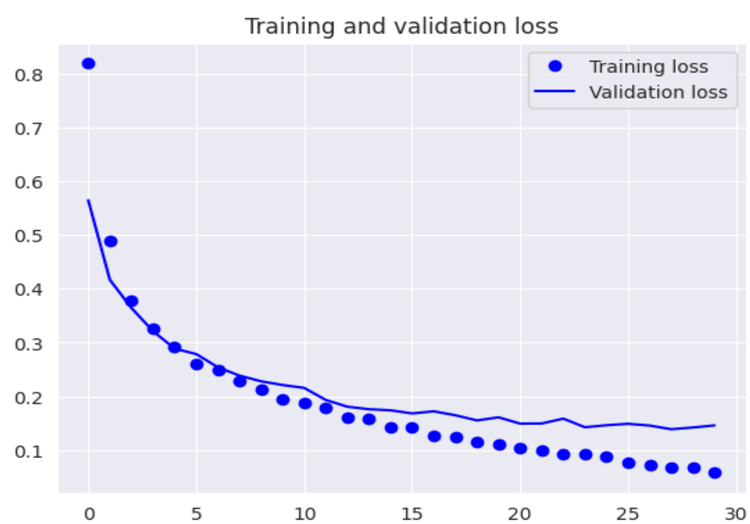
Second, a quantitative performance evaluation of the trained CNN model was conducted using the reserved testing set, which comprised 10% of the total dataset. The model's ability to generalize to unseen data was assessed using a standard set of classification metrics derived from the Confusion Matrix. These metrics included Accuracy, which measures the proportion of correct predictions overall; Precision, which evaluates the correctness of positive predictions; Recall (or Sensitivity), which measures the model's ability to identify all actual positive cases; and the F1-Score, which provides a harmonic mean of Precision and Recall, offering a balanced measure of performance, especially in cases of class imbalance. These metrics provided a comprehensive understanding of the model's diagnostic capabilities.

3. RESULTS AND DISCUSSION

This section presents the results from the model's training and evaluation, followed by a detailed discussion interpreting the significance of these findings.

3.1 Model Training Performance

The model's training process was monitored over 30 epochs, with the performance tracked using accuracy and loss metrics on both the training and validation sets, as illustrated in Figure 2. The validation accuracy rose rapidly and stabilized at a peak of approximately **95%**, while the validation loss flattened at a low value. The slight divergence between the training and validation curves indicates the presence of minor overfitting, which is common. However, the high and stable performance on the validation set confirms that the model achieved excellent convergence and developed strong generalization capabilities before final testing.



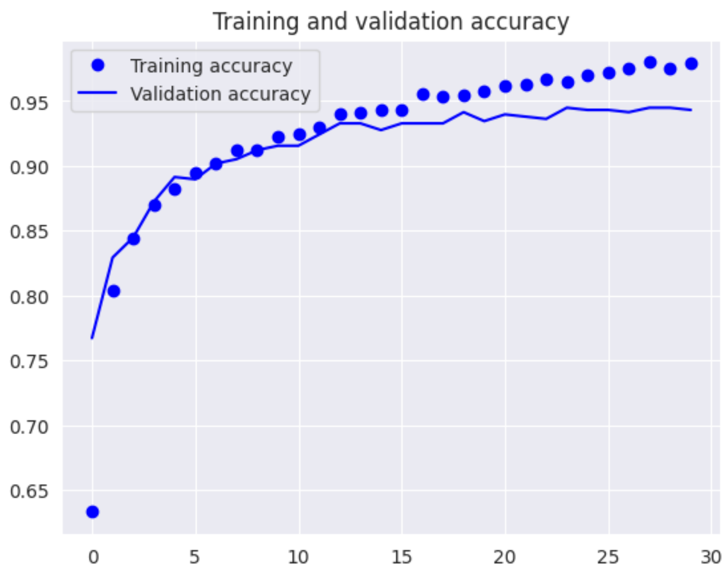


Figure 2. Training and Validation Accuracy and Loss Curves

3.2 Model Evaluation on Test Data.

The model's final performance was evaluated on the unseen test set, which consisted of 582 images. The model achieved a strong overall accuracy of 93% across the three classes. A detailed breakdown of the performance metrics for each class, including Precision, Recall, and F1-Score, is presented in the Classification Report (Table 2).

Table 2. Classification Report of Model Performance

	Precision	Recall	F1-Score	Support
Caries	0.92	0.94	0.93	268
No Caries	0.91	0.90	0.91	194
Not a Tooth	1.00	0.98	0.99	120
Average	0.93	0.93	0.93	582

3.3 Web Application Implementation

The trained CNN model was successfully implemented in a functional web application designed for accessibility and ease of use. The application provides an intuitive user interface for its primary workflow: static image upload. The process begins with the main prediction interface where users are prompted to upload a dental image (Figure 3).

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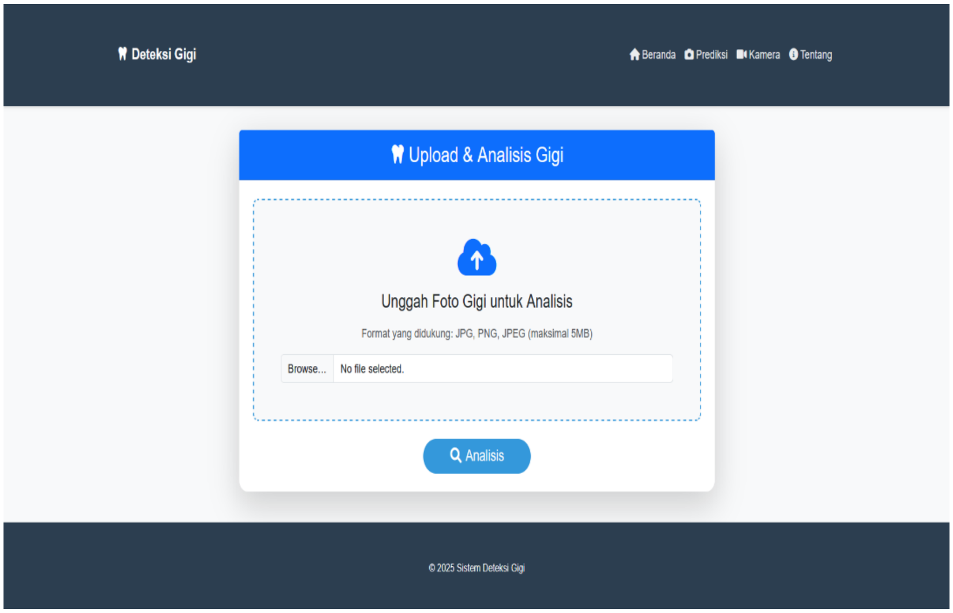

Figure 3. Image Upload Interface

Upon analysis, the system provides one of two distinct responses depending on the classification. For a valid dental image, the application displays the prediction result either 'Caries' or 'No Caries' along with a confidence percentage and relevant medical information regarding symptoms, causes, and potential treatments (Figure 4).

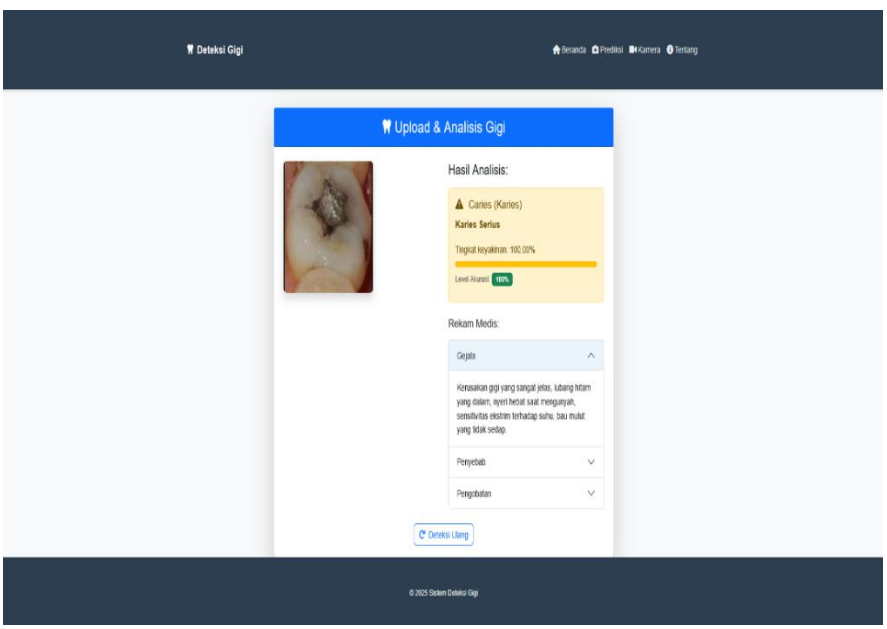

Figure 4. Prediction result for a valid dental image

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However, if the uploaded image is classified as 'Not a Tooth', the system displays an informational message clarifying that the image is not a valid tooth and advises the user to try again, thus ensuring robust error handling (Figure 5).

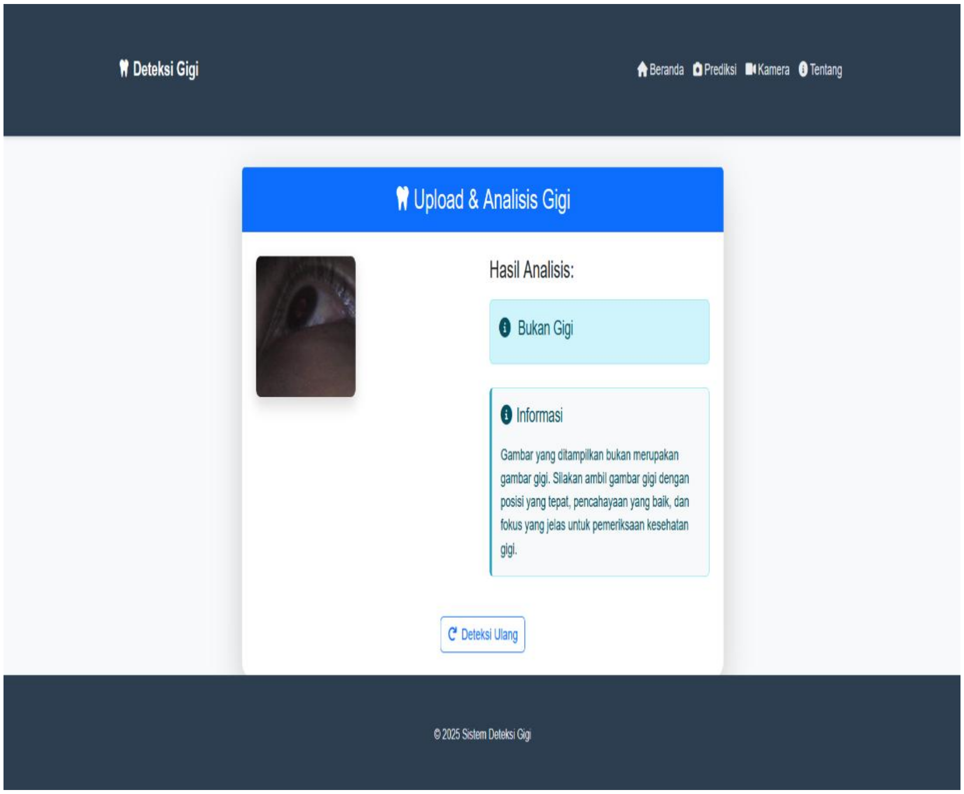

Figure 5. System response for a 'Not a Tooth' classification.

In addition to the static upload feature, the application's most interactive capability is its real-time detection, as shown in Figure 6. The system utilizes the device's camera to capture a live video stream of the user's teeth. Each frame from this stream is processed in real-time by OpenCV and passed to the CNN model for immediate inference. The model's prediction, including the classification label 'Caries', 'No Caries', or 'Not a Tooth' and the confidence score, is then dynamically overlaid onto the live video feed. This provides instant, continuous feedback to the user, allowing them to perform a quick and convenient self-screening by simply pointing their camera.

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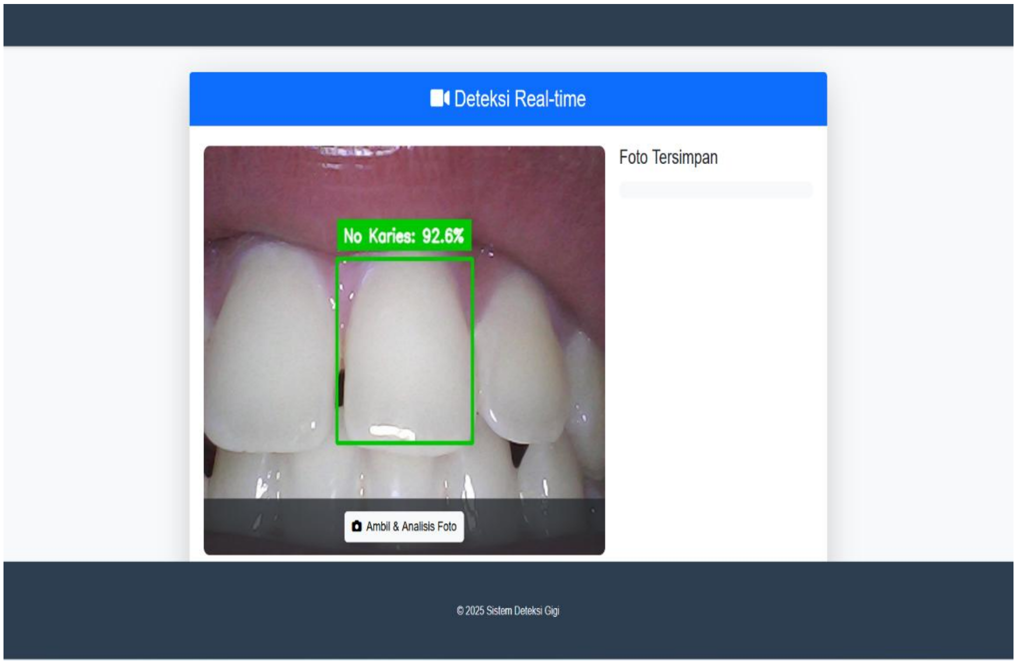

Figure 6. Real-time detection with prediction overlay

3.4 Discussion

The results of this study demonstrate that the CNN model, built upon the MobileNetV3 Small architecture with transfer learning, is highly effective for the three-class dental image classification task, achieving a strong overall accuracy of 93%. This performance is highly competitive and builds upon foundational work in this area, such as that by Lee et al. [14]. More importantly, our model's 93% accuracy not only aligns with this foundational work but also shows a measurable improvement over other recent, specialized studies. For instance, it directly surpasses the 92.5% accuracy reported in a recent study that also employed a deep learning approach for caries detection on similar intraoral photographs [15]. This comparison underscores the effectiveness of our chosen model architecture and robust three-class classification approach.

The most significant finding is the successful implementation and performance of the 'Not a Tooth' class, which achieved a precision of 1.00 and recall of 0.98. This confirms the model's exceptional capability to reject irrelevant inputs, a critical feature for a real-world application where users may upload imperfect images. By correctly identifying and filtering non-dental images, the system's robustness and reliability are significantly enhanced. Furthermore, the model maintained a high recall of 0.94 for the 'Caries' class, underscoring its effectiveness as a diagnostic support tool by successfully minimizing false negatives.

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Despite the promising results, this study has several important limitations that must be acknowledged. First, the model was trained and validated on a test set derived from the same initial dataset collection. It has not yet undergone formal clinical validation using a truly independent, external dataset collected directly from a diverse clinical environment. Therefore, while promising, its performance in a real-world clinical workflow remains unverified. Second, while the 'Not a Tooth' class enhances robustness, the model's precise generalization capabilities against images with *extreme* variations in focus, angle, and suboptimal lighting conditions—common issues with smartphone-based tele-dentistry—require further quantification. These challenges are not unique to this study; they reflect recognized, systemic limitations within the field, such as the widespread reliance on non-representative datasets and significant variations in imaging techniques, as highlighted in recent comprehensive reviews [16].

Therefore, future work should focus on several key areas. First, enriching the dataset with clinically validated images from diverse populations is essential to improve robustness. Second, future research could explore implementing segmentation features to precisely locate and highlight carious lesions on the tooth, a technique shown to provide more detailed diagnostic information [17]. Finally, developing a native mobile application could further enhance performance and accessibility.

4. CONCLUSION

In conclusion, this study successfully developed and validated a web-based system for a three-class dental caries detection task using a Convolutional Neural Network. The implemented model demonstrated strong performance, achieving an overall accuracy of 93.% and a critical recall of 0.94 for the 'Caries' class, confirming its potential as a diagnostic support tool. Crucially, the model's ability to accurately classify a 'Not a Tooth' category highlights its enhanced robustness for real-world application.

Furthermore, the model was successfully integrated into a functional and accessible web application with features for both static image upload and real-time detection. This research contributes a promising and practical tool for early caries screening that is more reliable against invalid user inputs, supporting the broader goals of tele-dentistry. Future work should focus on enriching the dataset with clinically validated data and expanding the model's capabilities to include segmentation features.

REFERENCES

[1] Zang, X., Luo, C., Qiao, B., Jin, N., Zhao, Y., & Zhang, H. (2022). A deep learning model using convolutional neural networks for caries detection and recognition with endoscopes. *Annals of Translational Medicine, 10*(24), 1369–1369.

[2] Dashti, M., Londono, J., Ghasemi, S., Tabatabaei, S., Hashemi, S., Baghaei, K., Palma, P. J., & Khurshid, Z. (2024). Evaluation of accuracy of deep learning and conventional neural network

algorithms in detection of dental implant type using intraoral radiographic images: A systematic review and meta-analysis. *Journal of Prosthetic Dentistry, 133*(1), 137–146.

[3] Widodo, C. E., Adi, K., & Gernowo, R. (2020). Medical image processing using python and open cv. *Journal of Physics: Conference Series, 1524*(1), 4–8.

[4] Oztekin, F., Katar, O., Sadak, F., Yildirim, M., Cakar, H., Aydogan, M., Ozpolat, Z., Talo Yildirim, T., Yildirim, O., Faust, O., & Acharya, U. R. (2023). An Explainable Deep Learning Model to Prediction Dental Caries Using Panoramic Radiograph Images. *Diagnostics, 13*(2).

[5] Park, E. Y., Cho, H., Kang, S., Jeong, S., & Kim, E. K. (2022). Caries detection with tooth surface segmentation on intraoral photographic images using deep learning. *BMC Oral Health, 22*(1), 1–9.

[6] Sharma, D., Kudva, V., Patil, V., Kudva, A., & Bhat, R. S. (2022). A Convolutional Neural Network Based Deep Learning Algorithm for Identification of Oral Precancerous and Cancerous Lesion and Differentiation from Normal Mucosa: A Retrospective Study. *Engineered Science, 18*, 278–287.

[7] Saini, D., Jain, R., & Thakur, A. (2021). Dental Caries early detection using Convolutional Neural Network for Tele dentistry. *2021 7th International Conference on Advanced Computing and Communication Systems, ICACCS 2021*, 958–963.

[8] Siji Rani, S., Garine, S., Janardhana, P. H., Reddy, L. L. P., Kumar, P. J. V., & Dwaz, C. G. (2024). Deep Learning-based Cavity Detection in Diverse Intraoral Images: A Web-based Tool for Accessible Dental Care. *Procedia Computer Science, 233*, 882–891.

[9] Garg, A., Lu, J., & Maji, A. (2023). Towards Earlier Detection of Oral Diseases On Smartphones Using Oral and Dental RGB Images. *ArXiv Preprint*.

[10] Rouhbakhshmeghrazi, A., & Alizadeh, G. (2024). Detecting dental caries with convolutional neural networks using color images. *ArXiv Preprint*.

[11] Alomar, K., Aysel, H. I., & Cai, X. (2023). Data Augmentation in Classification and Segmentation: A Survey and New Strategies. *Journal of Imaging, 9*(2).

[12] Howard, A., Sandler, M., Chu, G., Chen, L. C., Chen, B., Tan, M., ... & Adam, H. (2019). Searching for MobileNetV3. *In Proceedings of the IEEE/CVF international conference on computer vision* (pp. 1314-1324).

[13] Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

[14] Lee, J. H., Kim, D. H., & Jeong, S. N. (2018). Diagnosis of dental caries on intraoral camera images using a deep convolutional neural network. *Journal of Dentistry, 77*, 99-104.

[15] Kühnisch J, Meyer O, Hesenius M, Hickel R, Gruhn V. Caries Detection on Intraoral Images Using Artificial Intelligence. *Journal of Dental Research*. 2021;101(2):158-165. doi:10.1177/00220345211032524

[16] Nooraldaim, A., & Saed, A. (2023). Artificial Intelligence for Caries and Tooth Detection in Dental Imaging: A Review. *Indonesian Journal of Computer Science*, *12*(6). https://doi.org/10.33022/ijcs.v12i6.3522

[17] Cantu-Paz, F. J. G., & Lizárraga-Liceaga, M. (2021). Dental caries segmentation in bitewing radiographs using deep learning. *Applied Sciences, 11*(16), 7578.