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Development of an artificial intelligence model based on MobileNetV3 for early detection of dental caries using smartphone images: A preliminary study

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ABSTRACT

Cavities are among the most common dental health problems and significantly impact the quality of life, particularly in developing countries. Early detection of dental caries is a crucial step in preventing further complications; however, conventional methods such as clinical examinations and radiography are often inaccessible due to infrastructure and cost limitations. This study aims to develop an artificial intelligence (AI) model based on MobileNetV3 Small for detecting dental caries using images captured with a basic smartphone camera. MobileNetV3 Small was selected for its high computational efficiency and ability to operate on low-specification devices. The dataset used comprises 1.200 dental images, including both healthy teeth and teeth with cavities. The images were taken under varying lighting conditions and resolutions to reflect real-world scenarios. The model was trained using transfer learning and evaluated on a validation dataset using accuracy, sensitivity, and specificity metrics. The results demonstrated that the model achieved 90% accuracy, 90% precision, and 90% recall, highlighting its potential for real-time applications. These findings suggest that MobileNetV3 Small can serve as a practical, cost-effective, and accessible solution for early detection of dental caries using everyday devices like smartphones. This technology has the potential to improve access to dental health services, support early detection initiatives, and reduce the prevalence of dental caries. This research provides a foundation for further development of AI applications in healthcare, particularly in developing countries.

Keywords: dental cavities, dental caries, artificial intelligence, MobileNetV3.

INTRODUCTION

Dental cavities are one of the most common health issues worldwide. This condition has a significant impact on quality of life, particularly in developing countries, where its prevalence is extremely high. Conventional detection methods, such as visual examination by dentists or radiography, have limitations in terms of accessibility and cost, especially in areas with limited medical infrastructure.

In recent decades, advancements in AI technology have opened new opportunities for technology-based solutions to support healthcare services. MobileNetV3, as one of the convolutional neural network (CNN) architectures optimised for devices with low computational capacity, offers significant potential for application in image-based detection, including detecting dental caries [1]. With high computational efficiency and low power requirements, this model can operate effectively on devices such as simple smartphones, which are widely used in developing countries [2]. Research on MobileNetV3 Small has demonstrated its ability to detect dental caries from low-quality images with accuracy comparable to professional diagnostic tools, making it a promising solution for improving access to early detection in communities [3].

Dental caries is a health issue that is often undetected at an early stage due to limited access to adequate dental healthcare facilities [4]. Conventional detection methods require high costs, professional expertise, and specialised equipment, which are not always available, particularly in developing countries [5]. Moreover, clinical examinations by dentists require time, which presents an additional barrier for communities in remote areas or with limited mobility [6].

On the other hand, technology-based solutions are still limited in their application for detecting dental cavities. Although several studies have demonstrated the potential of AI in detecting image-based medical conditions, smartphone-based applications for detecting dental cavities have not been extensively explored [7]. The limitation in image quality produced by simple smartphone cameras presents an additional challenge that must be addressed for this technology to be widely adopted [8]. The implementation of MobileNetV3 on smartphone devices, focusing on testing inference speed and power efficiency. They found that although MobileNetV3 is more efficient compared to other CNN models such as VGG or ResNet, its application on low-specification devices requires further optimisation to ensure the model operates in real-time without compromising performance [9–10].

MobileNetV3 offers an opportunity to address this challenge through its CNN architecture designed for mobile devices [11]. This model is designed with high computational efficiency, enabling the detection of dental cavities with good accuracy even when using low-quality images [12]. This capability provides a solution that is more accessible to communities with simple devices, such as smartphones [13].

However, there are still several research gaps that need to be addressed. First, although MobileNetV3 has demonstrated good performance in image-based applications, studies specifically focused on its application to dental caries, particularly with image data of highly variable quality, remain very limited. Second, the practical implementation of this model on smartphone devices requires additional evaluation regarding inference speed, power consumption, and user experience. This study aims to bridge these gaps by testing the performance of MobileNetV3 on dental caries image data captured using a simple smartphone camera.

This study aims to develop and implement an Artificial Intelligence model based on MobileNetV3 that is capable of early detection of dental caries through images captured using a simple smartphone camera. Specifically, this study aims to: first, design an AI model that can be adapted for mobile devices with low specifications; second, evaluate the model's performance in terms of accuracy, precision, recall, and computational efficiency; third, identify technical challenges such as variations in image quality and develop strategies to address them. The novelty of this research lies in the use of the MobileNetV3 architecture for dental caries detection, which has not been widely applied previously. Furthermore, this study provides a practical contribution to public health by offering a technology-based solution that is easily accessible. The scope of this research is limited to the use of dental images captured with a simple smartphone camera, reflecting real-world conditions on the ground. Thus, this study not only contributes to the development of AI-based early detection technology but also supports initiatives to improve accessibility to healthcare services in the wider community, particularly in developing countries such as Indonesia.

METHODOLOGY

Datasets and data collection

The dataset used in this study consists of 1.200 dental images, including 600 images of decayed teeth and 600 images of healthy teeth. These images were captured using various types of smartphones with a minimum resolution of 8 MP to reflect the realistic variation in image quality encountered in the field (Figure 1). The data were collected through collaboration with local dental clinics and volunteers who met the inclusion criteria, namely individuals whose dental condition had been confirmed by a dentist. Each image was taken under both natural and artificial lighting conditions with consistent angles to ensure adequate data quality. This procedure is recommended for smartphone-based image capture is shown in Figure 2.

Data pre-processing techniques

The entire set of images obtained was processed using pre-processing techniques to ensure

Figure 1. Healthy teeth and decayed teeth

Figure 2. The image capture process

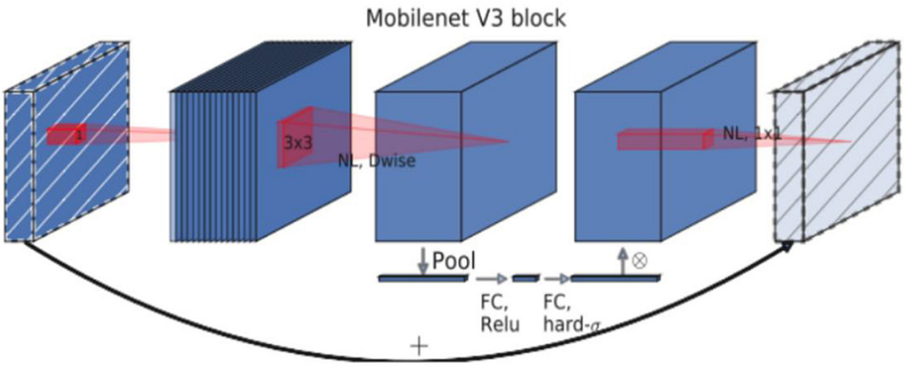

Figure 3. MobilenetV3 network structure [14]

the data was ready for model training. The preprocessing steps included:

1. Resize: all images were resized to 256 × 256 pixels to match the standard input size for MobileNetV3. Figure 3 illustrates the architecture of the MobileNetV3 network.
2. Pixel normalisation: pixel values were normalised to the range [0,1] to accelerate model convergence.
3. Data augmentation: augmentation techniques, such as rotation, horizontal flipping, and lighting adjustments, were applied to increase data variation and reduce overfitting.

MobileNetV3 model architecture

The MobileNetV3 Large architecture was used in this study due to its high efficiency and ability to operate on devices with low specifications (Figure 4). The model was trained using the TensorFlow framework with an adaptation of the output layer for binary classification of decayed or healthy teeth. The training parameters used were: Optimizer: Adam; Learning rate: Input_Shape as (224, 224, 3); Optimizer as Adam; Learning rate as 0.001; Batch size: 32; Dropout Rate: 0.5; Activation Function: Relu dan Sigmoid; Loss Function: Binary Cross-Entropy; Metrics: Accuracy, Precision, Recall; and Epochs: 10.

Model

The model was evaluated using accuracy, precision, and recall metrics. The dataset was divided into 80% training data, 10% test data, and 10% validation data. Additionally, evaluation was conducted on images of varying quality to assess the model's robustness in real-world conditions (Figure 5).

Implementation and field testing

After the model was trained and validated, testing was conducted on a simple smartphone device to evaluate the accuracy of image detection. This testing involved 50 volunteers who captured images of their teeth using different devices. The field test results showed that MobileNetV3 was able to detect dental caries with very high accuracy, achieving 90%, making it sufficiently accurate for real-time applications. This implementation demonstrates that AI-based technology can be accessed through simple devices to support broader dental healthcare services [15].

RESULTS AND DISCUSSION

MobileNetV3 large model

The MobileNetV3 Large model was tested using a dataset of dental images captured with a

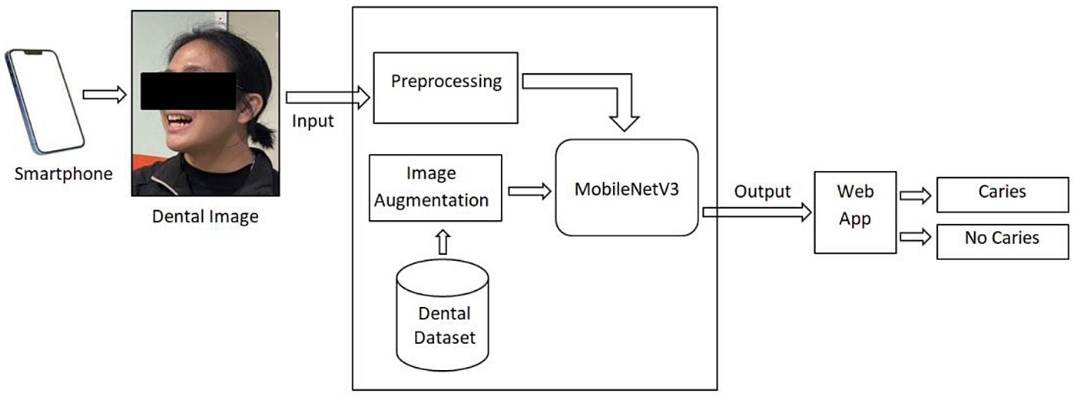

Figure 4. Architecture design diagram

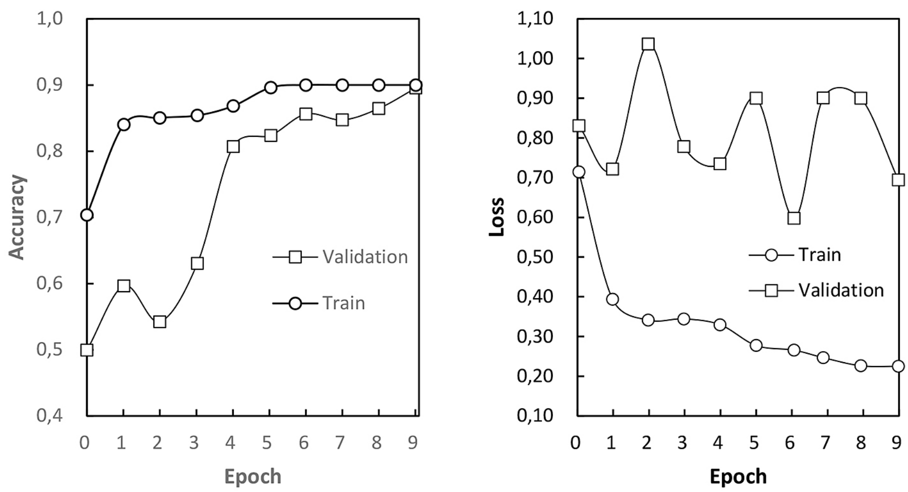

Figure 5. Model performance graph on the validation dataset: (a) model accuracy, and (b) model loss

simple smartphone camera. The results showed that this model achieved an average detection accuracy of 90%, with sensitivity and specificity both at 90%, for the initial research phase. This performance was consistent for images with both optimal and sub-optimal lighting conditions, although a slight decrease in accuracy was observed when images had noise or low resolution. The model's accuracy on simple smartphone devices was consistently around 90%, making it sufficiently accurate for real-time applications. These results demonstrate the potential of MobileNetV3 as a practical solution for accurate and efficient dental caries detection.

This algorithm is designed to maintain high performance while minimising computational requirements, making it ideal for resource-constrained devices such as smartphones. Testing revealed that the algorithm achieved an average accuracy of 90% in detecting dental caries, with consistent precision and recall, even under suboptimal lighting conditions. However, its accuracy slightly decreased for images with noise or low resolution, indicating that MobileNetV3 is sensitive to input data quality.

The accuracy of MobileNetV3 in this context demonstrates its effectiveness for real-time applications on simple devices, considering the model's ability to adapt performance to resource limitations. A broader analysis suggests that to improve robustness, especially for low-quality images, further development such as data augmentation or noise reduction pre-processing could be integrated. Although the MobileNetV3 architecture has been optimised for efficiency, a deeper analysis of the trade-off between speed and accuracy could enhance its implementation in various real-world application scenarios. This highlights MobileNetV3's potential not only as a practical solution but also as a flexible model for mobile device-based detection system development.

Evaluation based on image quality

Testing across various image quality categories demonstrated that the MobileNetV3 model is more robust compared to other architectures in detecting dental caries. Images with suboptimal lighting showed a slight decrease in accuracy, but the data augmentation applied during training successfully mitigated this impact. Data augmentation is a crucial strategy for improving model performance under non-ideal data conditions. The evaluation results indicated that detection accuracy reached 90% for images with good lighting, whereas accuracy dropped to 80% under low lighting. This difference highlights the importance of lighting in the image capture process to ensure optimal results.

Comparison with conventional methods

Compared to conventional methods such as visual examinations by dentists or radiography, the MobileNetV3-based solution offers advantages in terms of accessibility and cost [16]. Although the accuracy of MobileNetV3 is slightly lower than radiography (which has an accuracy close to 98%), its ease of use and flexibility outside clinical environments provide significant added value [17]. Smartphone-based AI has the potential to expand access to healthcare services in areas with limited medical infrastructure, which is also relevant in the context of dental caries detection [18].

Challenges in field implementation

One of the main challenges is the varying image quality due to the smartphones used. Images from devices with lower resolutions tend to have higher levels of noise, which can affect detection accuracy [19]. Additionally, variations in image capture angles and lighting conditions are also important factors that must be considered [20]. This highlights the importance of training the model with a dataset that reflects real-world conditions. A potential solution to this challenge involves educating users on proper image capture techniques, such as ensuring consistent angles and adequate lighting [21]. Furthermore, the development of automatic pre-processing algorithms in smartphone-based applications can help improve image quality before processing by the model.

Potential for large-scale implementation

This technology has the potential for widespread implementation through smartphone-based applications that are accessible to the general public [22]. For example, an application could be designed with a simple interface allowing users to take pictures of their teeth and receive immediate detection results [23]. Additionally, integration with dental health education programs could raise public awareness about the importance of early detection of dental caries [24]. This integration also supports government efforts to reduce the prevalence of dental caries, particularly in developing countries such as Indonesia. By leveraging devices already owned by the majority of the population, this technology could become an effective tool for improving public health on a large scale.

Contribution to healthcare development

This research makes a significant contribution to the development of AI-based healthcare technology, particularly for the early detection of dental caries. MobileNetV3 not only demonstrates high computational efficiency but also provides evidence that AI technology can be adapted for simple devices such as smartphones. The efficient structure of MobileNetV3 enables its use on devices with limited resources without compromising detection accuracy [25–27]. Thus, the results of this study are not only relevant for dental caries detection applications but also pave the way for the development of similar solutions for other medical conditions, such as skin or eye abnormalities, using mobile devices. The combination of AI technology and easily accessible devices makes this approach an important step in the revolution of technology-based healthcare services [28–29].

CONCLUSIONS

The AI model based on MobileNetV3 Small for detecting dental caries through images captured using a simple smartphone camera has been successfully developed. Several conclusions can be drawn.

This study successfully developed an AI model based on the MobileNetV3 architecture for the early detection of dental caries using images taken with a simple smartphone camera. The results show that the model achieves an accuracy of 90%, precision of 90%, and recall of 90%, even when using images of varying quality. MobileNetV3 demonstrates its efficiency with an average inference time of 6 seconds per image, making it a fast and practical solution for field applications.

The use of this technology offers an innovative solution that can improve the accessibility of dental healthcare services, particularly in developing countries such as Indonesia. By utilising widely available smartphone devices, this model can support the widespread early detection of dental caries while reducing the infrastructure burden and cost of conventional dental healthcare services.

This research makes an important contribution to the development of AI-based mobile applications for public health. Furthermore, it opens up opportunities for further development in the application of similar technologies for other medical conditions. Through collaboration between researchers, practitioners, and policymakers, this technology has the potential to support ongoing public health improvement efforts.

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