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AI-Powered Mobile Application for Early Detection of Dental Diseases Using Intraoral Imaging

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Abstract

Oral health constitutes a fundamental component of overall well-being, with numerous systemic diseases, such as cardiovascular disorders, diabetes mellitus, and respiratory tract infections, being directly or indirectly associated with oral conditions. Delays in the diagnosis and treatment of dental diseases not only exacerbate oral complications but may also contribute to the progression of these systemic disorders, increasing both individual health burdens and the strain on healthcare systems. Recent advancements in artificial intelligence (AI), particularly in the domain of medical image analysis, have demonstrated significant potential in enhancing diagnostic accuracy and speed. Dentistry, which heavily relies on the visual assessment of intraoral structures, presents a promising field for the integration of AI-driven diagnostic tools. The use of AI can facilitate early detection of dental anomalies, enable timely intervention, and reduce the dependency on specialized clinical settings for initial screening. This study proposes the development of an AI-based mobile application that utilizes the ResNet50 model to detect common dental diseases through the analysis of intraoral photographs captured by users. Our model achieved an accuracy of 99.00%, a precision of 0.99, a recall of 0.99, and an F1-score of 0.99 on the test dataset. The application enables individuals to upload images of their oral cavity, receive automated diagnostic feedback, and, if necessary, schedule dental appointments based on the identified conditions. The integration of such a system into daily healthcare routines empowers users with accessible, real-time dental evaluations while supporting dental professionals in prioritizing patient care based on objective findings. By promoting early diagnosis and preventive care, the proposed solution not only contributes to improved oral and systemic health outcomes but also aligns with contemporary efforts to digitalize and optimize healthcare delivery through mobile and intelligent technologies.

1. Introduction

Oral and dental health plays a critical role not only in maintaining the integrity of the oral cavity and dentition but also in maintaining overall holistic health. A growing number of studies have demonstrated strong associations between oral diseases and a variety of conditions such as cardiovascular diseases, diabetes mellitus and respiratory infections. Dental diseases are often overlooked in the early stages despite these important associations due to their asymptomatic or mild course. This delay in diagnosis can lead to the progression of oral pathologies, making treatment difficult, increasing healthcare costs, and negatively affecting the quality of life of patients.

In recent years, Artificial Intelligence (AI) has emerged as a transformative force in healthcare, as in every field, and has offered promising solutions to improve diagnostic efficiency and accuracy. In particular, deep learning and computer vision techniques have shown remarkable success in analyzing medical images and outperformed traditional methods in many diagnostic processes. In disciplines such as dentistry, where clinical assessments are predominantly visual, the integration of AI-based diagnostic tools has the potential for significant improvement in early detection and intervention strategies.

This study proposes the design and development of a mobile application that uses AI-assisted image analysis to detect dental diseases through intraoral photographs submitted by users. The application is designed as a user-friendly platform that not only enables individuals to

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upload intraoral images and receive diagnostic feedback but also facilitates access to dental care by offering appointment scheduling features based on the analysis results. By enabling early diagnosis and timely intervention, the system aims to reduce the burden of untreated dental conditions, improve patient outcomes, and increase the efficiency of oral health services. The key contributions of this study are as follows:

1. *Development of an AI-powered mobile application*: We propose the design and implementation of a mobile application that utilizes artificial intelligence to detect common dental diseases through intraoral images captured by users. This application enables early diagnosis and timely intervention, empowering individuals with accessible and real-time dental evaluations.
2. *Integration of ResNet50 for disease detection*: The study demonstrates the effectiveness of the ResNet50 model in detecting dental diseases such as Tooth Discoloration, Mouth Ulcer, Hypodontia, Gingivitis, and Caries. The model achieves an impressive accuracy of 99.00%, highlighting its potential for real-world applications.
3. *Comprehensive dataset utilization*: The study leverages the "Oral Diseases" dataset obtained from Kaggle, which includes over 10,000 intraoral images across five disease classes. The dataset is preprocessed and fine-tuned to ensure optimal performance of the AI model.
4. *User-Friendly features for enhanced healthcare*: The mobile application integrates practical functionalities such as user registration, historical data tracking, and appointment scheduling with dental professionals. These features bridge the gap between early detection and professional care, improving patient outcomes.
5. *Validation against state-of-the-art models*: The proposed ResNet50 model outperforms existing state-of-the-art approaches, including MobileNetV3-Small, Attention U-Net-VGG16, and Mask R-CNN, in terms of accuracy and balanced performance across all disease classes. This underscores the robustness and reliability of our approach.
6. *Potential for digital healthcare transformation*: By promoting early diagnosis and preventive care, the proposed solution contributes to improved oral and systemic health outcomes. It aligns with contemporary efforts to digitalize and optimize healthcare delivery through mobile and intelligent technologies.

2. Literature Review

The use of artificial intelligence applications to protect dental health and improve treatment processes has increased rapidly in recent years. Especially in the detection of dental caries and early diagnosis of dental diseases, deep learning methods offer an important solution. Some studies in this field in the literature are summarized below.

Schwendicke et al. (2021) evaluated the cost-effectiveness of artificial intelligence-based systems on the detection of proximal caries in their study. In the analyses, it was shown that AI-assisted diagnostic methods, especially in the detection of early caries, both provide diagnostic accuracy and reduce costs in the long term compared to traditional methods. Economic modeling over different scenarios in the study revealed that AI-assisted diagnosis both improves clinical outcomes and optimizes resource use. These findings suggest that the integration of AI technologies into dental practice can both improve the quality of patient care and provide economic benefits to the healthcare system [1].

Cantu et al. (2020) investigated the detection of caries lesions at different stages on bitewing radiographs using deep learning methods. In the study, the extent to which carries lesions of various radiographic widths can be accurately classified by artificial intelligence models was evaluated and the performance of these models was compared with the evaluations of expert dentists. The results showed that deep learning-based systems can achieve high sensitivity and specificity rates, especially in early-stage caries. These findings revealed that artificial intelligence-supported analyses can be an effective support tool in caries diagnosis and can strengthen clinical decision processes [2].

Srivastava et al. (2017) used deep learning methods to detect dental caries on more than 3000 bitewing radiographs. The study evaluated the effectiveness of deep neural networks in the classification of caries and showed that these methods can work with accuracy close to human performance. This study is one of the early applications demonstrating the potential of AI in the field of radiographic image analysis [3].

Lee et al. (2018) investigated the use of a convolutional neural network (CNN) based deep learning algorithm for dental caries diagnosis. The model trained on clinically labeled dental images was shown to detect caries with similar accuracy to human experts. This study demonstrates that deep learning can be integrated into diagnostic support systems in dentistry [4].

Revilla-León et al. (2022) systematically reviewed the applications of artificial intelligence in restorative dentistry. By analyzing current studies in the literature, they evaluated how AI is used in areas such as planning, design, and fabrication of dental restorations. The findings showed that AI can improve accuracy in restorative processes and speed up the treatment process [5].

Samadzadegan et al. (2003) developed a method for automatic registration of dental radiograms. The study presented an early example of image processing techniques aimed at improving the accuracy of comparative analysis of dental images. This approach is considered one of the foundations of image analysis in digital dentistry [6].

Takahashi et al. (2021) conducted a study on the detection of dental prostheses and restorations using deep learning algorithms. The developed model was able to successfully distinguish and classify dentures and restorative materials in dental radiographs. This study shows that AI can be an effective tool for automatic recognition of dental inventories [7].

Lee et al. (2019) developed a deep convolutional neural network-based computer-aided diagnosis system for the detection of osteoporosis on panoramic radiographs. The study highlights the multidisciplinary diagnostic potential of dental images by demonstrating that systemic diseases can be identified from intraoral images. Preliminary results show that the system shows promising performance in bone density analysis [8].

Bilgir et al. (2021) focused on automatic tooth detection and numbering in panoramic radiographs by developing an artificial intelligence-based approach. The developed system utilized deep learning techniques to determine the location of teeth and classify them according to the universal tooth numbering system. It was shown that the model used in the research can work with high accuracy rates in individuals with different age groups and dental variations. The findings of the study demonstrate the feasibility of automated diagnostic support systems that save time and reduce human error in clinical dentistry [9].

Table 1 provides a comparative overview of various deep learning-based approaches employed for the detection of dental diseases. The summarized studies demonstrate the effectiveness of different CNN architectures, highlighting their high accuracy, precision, and sensitivity in diagnostic tasks. These findings underscore the growing potential of AI-driven methodologies in improving diagnostic reliability in dental radiographic analysis.

Table 1. Some models used in the detection of dental diseases.

Researchers	**Method**	**Results**
Durmuş et al. (2024) [10]	ResNet-based PSPNet	92.09% F1-score, 93.88% precision, 90.39% recall
Ünsal & Adem (2023) [11]	Faster R-CNN and YOLOv5	Faster R-CNN: 86.7% accuracy, YOLOv5: 92.7% accuracy
Çelik et al. (2019) [12]	GoogleNet Inception v3 CNN	94.7% training accuracy, 75% test accuracy
Wang et al. (2020) [13]	CNN-based hybrid model	Accuracy and specificity >90%
Lee et al. (2018) [14]	CNN (Deep Learning)	Premolarlar: 82.8% accuracy, 95% CI: 70.1%–91.2% Molarlar: 73.4% accuracy, 95% CI: 59.9%–84.0%
Schwendicke et al. (2020) [15]	Resnet18, Resnext50	AUC: 0.74 (0.66-0.82), Sensitivity: 0.59, Specificity: 0.76, PPV: 0.63, NPV: 0.73
Tuzoff et al. (2019) [16]	CNN (VGG-16)	98.00% sensitivity, 99.94% specificity in tooth numbering
Beser et al. (2024) [17]	YOLOv5	Sensitivity: 0.99, Precision: 0.99, F1-score: 0.99, mAP-0.5: 0.98
Hua et al. (2025) [18]	YOLO-DentSeg	mAP50 (Box) and mAP50 (Seg) scores of 0.870 and 0.855
Hasnain et al. (2024) [19]	CNN-based classifier	Accuracy: 97.87% and F1 score: 60%
Mei et al. (2023) [20]	YOLOrtho (YOLOv5 + CoordConv)	AP-Quadrant: 0.414, AP-Diagnosis: 0.357
Haghanifar et al. (2020) [21]	PaXNet (Ensemble Transfer Learning + Capsule Network)	86.05% accuracy, 69.44% and 90.52% recall for mild and severe caries, respectively

Recent literature reviews reveal that artificial intelligence-based systems have made significant advances in the detection and diagnosis of dental diseases. In particular, deep learning methods offer significant support to dentists in the evaluation of various dental problems such as caries detection, denture identification, lesion diagnosis and osteoporosis. Studies performed with neural network-based models often provide higher accuracy, precision and reliability values compared to human experts. In recent studies, impressive achievements have been obtained with different architectures such as ResNet, GoogleNet, Inception v3, YOLOv5, Faster R-CNN, and VGG-16. For example, Durmuş et al. (2024) obtained 92.09% F1 score, 93.88% precision and 90.39% recall rate with a ResNet-based PSPNet model. Similarly, Tuzoff et al. (2019) achieved 98% sensitivity and 99.94% specificity in tooth numbering with VGG-16 architecture. In addition, Çelik et al. (2019) achieved 94.7% accuracy on training data and 75% accuracy on test data using Inception v3.

Furthermore, imaging techniques such as bitewing and panoramic radiographs offer significant advantages in terms of early diagnosis, and the integration of deep learning algorithms with such data increases the effectiveness of clinical decision support systems. In this context, deep learning models not only increase diagnostic accuracy but also improve clinical processes by providing time-saving and reproducible analysis.

3. Methodology and Implementation

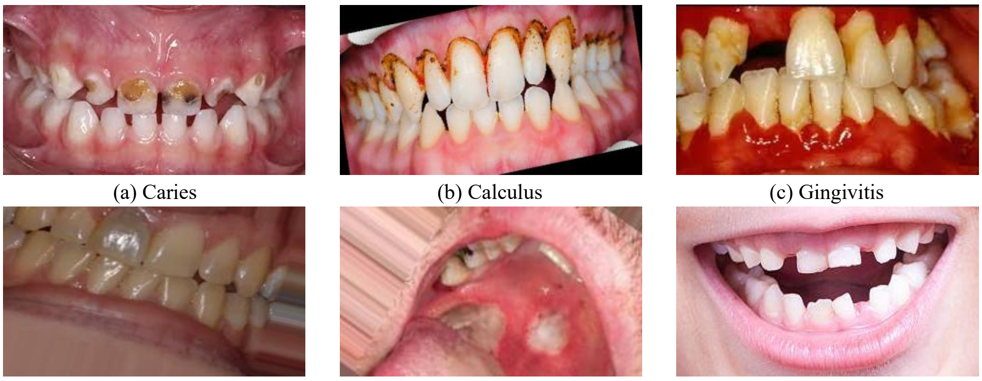
In this section, we detail the methodology and tools employed in the development of the AI-powered mobile application for early detection of dental diseases. The process encompasses the selection and preprocessing of the dataset, the implementation of deep learning models, and the integration of the trained model into a user-friendly mobile application. By utilizing advanced AI techniques and modern software frameworks, we aimed to create a robust system capable of analyzing intraoral images and providing accurate diagnostic feedback. Below, we first describe the dataset used for training and testing the models.

3.1. Dataset

The dataset used in this study is named "Oral Diseases" and was obtained through the Kaggle platform [22]. This dataset comprises six classes: 'Caries' (images showing tooth decay, cavities, or carious lesions), 'Calculus' (images depicting dental calculus or tartar buildup on teeth), 'Gingivitis' (images displaying inflamed or infected gums), 'Tooth Discoloration' (images showcasing tooth discoloration or staining), ' Mouth Ulcer ' (images exhibiting oral ulcers or canker sores), and 'Hypodontia' (images representing the condition of missing one or more teeth). The dataset contains a total of 11,523 images; however, due to high confusion between the 'Gingivitis' and 'Calculus' classes, which negatively impacted classification accuracy, the 'Calculus' class was excluded from the analysis. After this adjustment, the dataset contained 10,359 images, distributed as follows:

- Tooth Discoloration: 1,800 images
- Mouth Ulcer: 2,500 images
- Hypodontia: 1,200 images
- Gingivitis: 2,400 images
- Caries: 2,459 images

The images in the dataset have varying resolutions. All images in the dataset were resized to 256x256 pixels to ensure compatibility with the input requirements of the ResNet50 model. This standardization step is crucial for maintaining consistency in the model's input dimensions and optimizing computational efficiency during training. The dataset was split into training, validation, and test sets at an 80-10-10 ratio. Figure 1 shows the sample images from the Oral Diseases dataset.



(a) Caries (b) Calculus (c) Gingivitis
(d) Tooth Discoloration (e) Mouth Ulcer (f) Hypodontia

Figure 1. Sample images for each class in the Oral Diseases dataset [22].

3.2. Proposed Methodology

In this study, various deep learning models were evaluated for the detection of dental diseases using intraoral images. The selection of an appropriate model was crucial to ensure high accuracy and efficiency in diagnosing common oral conditions such as tooth discoloration, mouth ulcers, hypodontia, gingivitis, and caries. Below, we provide a concise overview of the models considered, their advantages and disadvantages, and the rationale behind selecting ResNet50 as the final model.

Experiments were conducted on different deep learning models for the detection of dental diseases. The success of the models is tested based on the dataset used, and accuracy and loss values are considered in performance evaluations. Popular models such as Xception, InceptionV3, MobileNetV2, EfficientNetB0 and ResNet50 are analyzed. Each model is trained with different epoch numbers and batch sizes and the results are compared.

Xception was developed by Google as an advanced version of the Inception architecture. It has 71 layers deep, deeply separable convolution and an efficient structure that connects convolution blocks with short paths like in ResNet. Thanks to the structure, Xception outperforms InceptionV3 on the ImageNet ILSVRC and JFT datasets. [23].

MobileNetV1 is a low memory consumption deep learning model developed by Google in 2017 for mobile and embedded devices [24]. MobileNetV2 is a more efficient version of MobileNetV1 and is enhanced with inverted residual structures and bottlenecks. This model increases the channel width by using 1x1 convolution operations for feature extraction and 3x3 depth convolution for feature extraction. In addition, inverted structures improve the stability of the model while increasing the learning speed [25].

EfficientNet is an architecture proposed by Tan and Le in 2019. The EfficientNet family uses a simple and effective scaling coefficient to achieve efficient performance by balancing network sizes. This coefficient improves the performance of the model by optimizing the network's parameters such as width, depth and resolution. EfficientNetB0 uses MBConv blocks, and the input data is subjected to MBConv1 and MBConv6 blocks after convolution [26].

InceptionV3 has a depth of 48 layers and uses inception modules consisting of 1x1, 3x3 and 5x5 convolutional composite layers. In this model, two or three 3x3 convolutions are applied instead of 5x5 and 7x7 convolutions. This reduces the number of parameters and speeds up the training time. The goal of InceptionV3 is to optimize the depth and width of the network to ensure efficient information flow through the network. As the depth of the network increases, its width increases in direct proportion [27].

ResNet50 is an architecture that eliminates the assumption that better results will be achieved in training with an increase in the number of layers. In the ResNet structure, “residual” blocks are used to ensure that the learning process continues after each block. Thanks to these blocks, even if the training fails, learning continues with the information from the previous layer [28]. ResNet is an innovative approach that aims to solve the difficulties encountered in the training process of deep convolutional neural networks, such as over learning and verification losses. This model increases accuracy rates by making it easier to tackle complex tasks. ResNet50 has a residual network structure consisting of 50 layers, which provides improved accuracy [29]. The ResNet50 model is named after its 50 layers. In its structure, there are 1x1, 3x3 and 1x1 convolution layers respectively. By reducing the number of parameters, the computational load is reduced and the error rate of the model is greatly reduced. This architecture was developed to solve the problem of performance degradation in convolutional neural networks [30].

To determine the most suitable model for our task, experiments were conducted using different deep learning architectures with varying hyperparameters. The models were trained on the Oral Diseases dataset, and their performances were evaluated based on metrics such as accuracy, loss. Each model was trained for a maximum of 50 epochs with batch sizes ranging from 16 to 64. Early stopping was implemented to prevent overfitting. The results of these experiments are summarized in Table 2, which compares the performance of each model under different configurations.

Table 2. Comparative analysis of model performance for model selection.

Model	Epoch	Batch size	Loss	Accuracy
Xception	20	32	0.6281	0.7332
Xception	10	32	0.7031	0.7269
InceptionV3	20	16	0.3486	0.7790
InceptionV3	50	32	0.3451	0.8121
InceptionV3	10	32	0.2602	0.8450
MobileNetV2	20	32	0.3624	0.8678
MobileNetV2	35	32	0.3061	0.8737
MobileNetV2	64	64	0.1385	0.9688
EfficientNetB0	10	32	0.1385	0.9688
ResNet50	10	32	0.1294	0.9431
ResNet50	12	32	0.1214	0.9439

From these experiments, it was observed that both EfficientNetB0 and ResNet50 achieved high accuracy rates with relatively low loss values. However, ResNet50 demonstrated superior performance in terms of balancing accuracy and computational efficiency, particularly when considering the complexity of dental disease detection tasks.

ResNet50 model's residual architecture allowed for effective learning of intricate patterns in intraoral images, leading to reliable disease detection. During validation, ResNet50 showed strong generalization abilities, maintaining high performance even on unseen data. This is critical for real-world applications where variability in image quality and disease manifestations is high. While ResNet50 requires more computational resources than lighter models like MobileNetV2 or EfficientNetB0, its performance gains justify the trade-off. Additionally, modern mobile platforms and cloud-based solutions enable efficient deployment of such models without significant latency. ResNet50's pre-trained weights provided a strong initialization point, allowing us to achieve high accuracy with fewer training epochs compared to training from scratch. This reduced the risk of overfitting and accelerated the development process.

By carefully evaluating these factors, ResNet50 emerged as the optimal choice for our AI-powered mobile application, ensuring both high diagnostic accuracy and practical usability.

3.3. Implementation Details

The implementation of the proposed system involved the integration of various software tools and frameworks to ensure seamless functionality across model training, validation, and deployment. The following sections detail the key components and their roles in the development process.

3.3.1. TensorFlow and Python for Model Training

The deep learning model was developed using TensorFlow, a widely adopted open-source library for machine learning and artificial intelligence. TensorFlow's robust support for convolutional neural networks (CNNs) enabled efficient training, validation, and testing of the model. The programming language Python served as the foundation for implementing the model, leveraging its simplicity, versatility, and extensive library ecosystem. Python's compatibility with TensorFlow facilitated rapid prototyping and optimization of the model architecture, significantly enhancing the development workflow.

3.3.2. Flutter for Mobile Application Development

The mobile application was developed using Flutter, a cross-platform framework that supports the creation of applications for both Android and iOS devices. Flutter's widget-based architecture allowed for the design of an intuitive and visually appealing user interface. Additionally, its hot-reload feature accelerated the development process by enabling real-time updates during the coding phase. The framework's ability to deliver consistent performance across platforms ensured a smooth user experience.

3.3.3. Firebase for Backend Services

Backend functionalities were implemented using Firebase, a comprehensive platform designed for managing application data and services. Firebase provided essential features such as user authentication, secure data storage, push notifications, and real-time data synchronization. These capabilities enhanced the application's usability by ensuring reliable user management and seamless interaction between the frontend and backend components. Furthermore, Firebase's scalability and ease of integration made it an ideal choice for supporting the application's operational requirements.

3.3.4. Flask API for Model Integration

To bridge the gap between the trained deep learning model and the mobile application, a Flask API was developed. Flask, a lightweight and flexible web framework written in Python, was utilized to handle HTTP requests and facilitate data exchange in JSON format. The API served as an intermediary, allowing the mobile application to send intraoral images to the server and receive diagnostic predictions from the ResNet50 model. This modular approach ensured efficient communication between the client-side application and the server, enabling real-time analysis and feedback for users.

4. Results and Discussion

This section presents the outcomes of the study, focusing on the performance of the ResNet50 model in detecting dental diseases through intraoral images. The results are discussed in terms of training and testing accuracy, model validation, and real-world applicability within the mobile application. By analyzing key metrics such as accuracy, precision, recall, and F1-score, we aim to demonstrate the robustness and reliability of the proposed system. Additionally, the challenges encountered during implementation, along with potential improvements, are addressed to provide a comprehensive understanding of the model's capabilities and limitations. This discussion not only highlights the success of the AI-powered solution but also offers insights into its future development and integration into clinical workflows.

4.1. Training and Testing Results

The performance of the ResNet50 model during the training and testing phases was rigorously evaluated to ensure its suitability for detecting dental diseases from intraoral images. The ResNet50 architecture, a state-of-the-art convolutional neural network (CNN), was chosen for its ability to address common challenges in deep learning, such as vanishing gradients and overfitting, while maintaining high accuracy and computational efficiency.

ResNet50 is a 50-layer residual network that introduces residual blocks to facilitate the flow of information across layers. These blocks enable the network to learn identity mappings, allowing it to bypass certain layers when necessary. This innovation addresses the degradation problem often encountered in very deep networks, where adding more layers can lead to diminished performance [29]. In the context of dental disease detection, ResNet50's residual connections proved instrumental in capturing intricate patterns in intraoral images, such as subtle lesions or discolorations, without compromising computational efficiency.

There are five convolutional blocks between layers in the ResNet50 architecture. These blocks have dimensions of 1x1, 3x3 and 1x1, and the input images are reduced to lower dimensions with 1x1 convolution blocks, followed by high-dimensional filtering with 3x3 convolution blocks. The dimension reduction is performed with a global average pool layer. The final layers of the architecture are fully connected layers that use the Softmax activation function to classify 1000 different categories. ResNet50 has a total of 25.6 million parameters and the architecture of this model is shown in Figure 2. The functional part of this structure includes the convolution, activation and pooling layers. Then, flattening is performed with the Flatten operation and the result is passed to the two-layer fully connected layer [31].

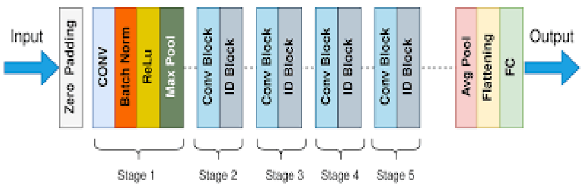


Figure 2. ResNet50 architecture [32].

The preprocessing pipeline was designed to ensure consistency and compatibility of the input data with the ResNet50 architecture. The following steps were applied to each image in the dataset:

1. Resizing: All images were resized to 256x256 pixels to standardize their dimensions for the ResNet50 input layer.
2. Normalization: Pixel values were scaled to the range [0, 1] by dividing each value by 255, ensuring that the input data was normalized and suitable for deep learning models.
3. Data augmentation: To enhance the robustness of the model, data augmentation techniques were applied during training. These included random rotations, horizontal flipping, zooming, and slight shifts in both vertical and horizontal directions. This helped the model generalize better across diverse image conditions.
4. Class balancing: Due to class imbalance in the dataset, oversampling techniques were applied to ensure equal representation of each class during training. This step significantly improved the model's ability to handle underrepresented classes.

The model was trained using pre-trained weights on the ImageNet dataset, enabling transfer learning to accelerate convergence and improve generalization. The last 10 layers of the model were fine-tuned to adapt to the specific characteristics of the "Oral Diseases" dataset. Customization included the addition of GlobalAveragePooling2D, Dense layers, and Dropout layers to enhance the model's robustness and prevent overfitting. The final layer was configured with the Softmax activation function to handle the five target classes: 'Tooth Discoloration', 'Mouth Ulcer', 'Hypodontia', 'Gingivitis', and 'Dental Caries'.

The ResNet50 model was initialized with pre-trained weights from the ImageNet dataset to leverage transfer learning. To adapt the model to the specific characteristics of the 'Oral Diseases' dataset, the following modifications were made:

- Fine-Tuning: The last 10 layers of the ResNet50 model were fine-tuned, including the fully connected layers and the classification head. This allowed the model to learn domain-specific features while retaining the general knowledge acquired from ImageNet.
- Global Average Pooling Layer: A GlobalAveragePooling2D layer was added after the convolutional blocks to reduce the spatial dimensions of the feature maps.
- Dropout Layer: A Dropout layer with a rate of 0.5 was introduced to prevent overfitting during training.
- Output Layer: The final output layer was replaced with a Dense layer containing five neurons (one for each disease class) and a Softmax activation function to handle multi-class classification.

These modifications ensured that the model was optimized for the task of detecting dental diseases while maintaining computational efficiency. The model was compiled using the Adam optimizer and the loss function 'sparse categorical crossentropy'. During training, metrics such as accuracy and loss were monitored to evaluate the model's progress. To optimize training time and mitigate overfitting, early stopping was implemented. This technique terminated training at epoch 15, significantly earlier than the initially planned 50 epochs, while still achieving optimal performance.

The graphs presented in Figure 3 illustrate the training and validation accuracy and loss metrics across epochs. These visualizations provide a comprehensive understanding of the model's performance over time, enabling a more detailed evaluation of its learning progression.

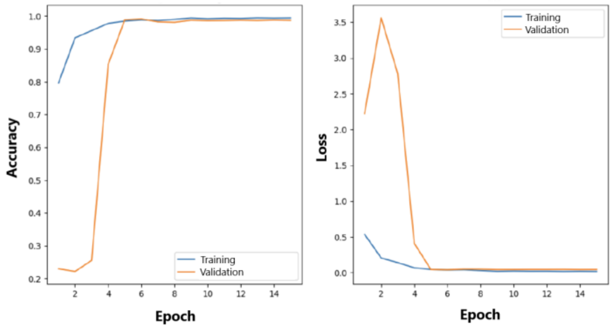


Figure 3. Accuracy and loss curves of ResNet50 model training on the oral diseases dataset.

The ResNet50 model demonstrated exceptional performance in both training and validation phases, with training accuracy (blue line) and validation accuracy (orange line) showing a consistent upward trend that converged closely, indicating effective learning without overfitting. This was further supported by the steady decline in both training and validation loss, reflecting the model's ability to minimize prediction errors. Early stopping at epoch 15 optimized performance by halting training when validation metrics flattened out, achieving a test accuracy of 99.00% with a low loss of 0.0329. During training, the model reached an even higher accuracy of 99.47% and a loss of 0.0163, demonstrating its strong learning capability. These results highlight the model's robustness and generalization ability for dental disease detection, confirming its effectiveness for real-world applications.

The model achieved balanced performance across all disease categories, with precision, recall, and F1-score values exceeding 98% for most classes. These metrics are calculated as follows:

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F_1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{3}$$

Table 3 presents the class-specific performance metrics of the proposed model, including Precision, Recall, and F1-Score. Precision reflects the model's ability to minimize false positives, while Recall indicates its effectiveness in identifying true positives. The F1-Score provides a balanced evaluation by harmonizing these metrics.

Table 3. Performance results of the ResNet50 model for oral disease classes.

Class	Precision	Recall	F1	Support
Tooth Discoloration	0.98	1.00	0.99	185
Mouth Ulcer	1.00	1.00	1.00	255
Hypodontia	0.99	0.96	0.98	126
Gingivitis	0.97	0.99	0.98	236
Dental Caries	1.00	0.98	0.99	239
Accuracy			0.99	1041
Macro Average	0.99	0.99	0.99	1041
Weighted Average	0.99	0.99	0.99	1041

The performance metrics presented in Table 4 provide a comprehensive evaluation of the ResNet50 model's ability to classify dental diseases accurately. The model demonstrates exceptional performance across all classes, with Precision, Recall, and F1-Score values exceeding 98% for most categories. For instance, the model achieves perfect scores (1.00) for both Precision and Recall in the Mouth Ulcer class, indicating flawless classification for this category. Similarly, Tooth Discoloration, Hypodontia, Gingivitis, and Dental Caries exhibit high performance metrics, with only minor trade-offs in Recall or Precision for some classes, such as Hypodontia, which has a slightly lower Recall of 0.96. These variations are minimal and do not significantly impact the overall effectiveness of the model.

The Support column represents the number of samples in the test dataset for each class, ranging from 126 samples for Hypodontia to 255 samples for Mouth Ulcer. Despite differences in sample sizes, the model maintains balanced performance, as evidenced by the high Macro Average and Weighted Average scores. The overall accuracy of 0.99 underscores the model's ability to generalize well to unseen data, confirming its reliability in real-world applications. Additionally, the alignment of the Macro Average and Weighted Average metrics highlights that the model handles class imbalances effectively, ensuring consistent performance across all categories. These results validate the robustness of the ResNet50 architecture in detecting dental diseases with high precision and reliability.

Figure 4 shows the prediction results of the ResNet50 for the dental diseases. These were obtained using test images of five different dental disease classes from the oral diseases dataset used in this study. The model output refers to the class that shows the highest classification accuracy.

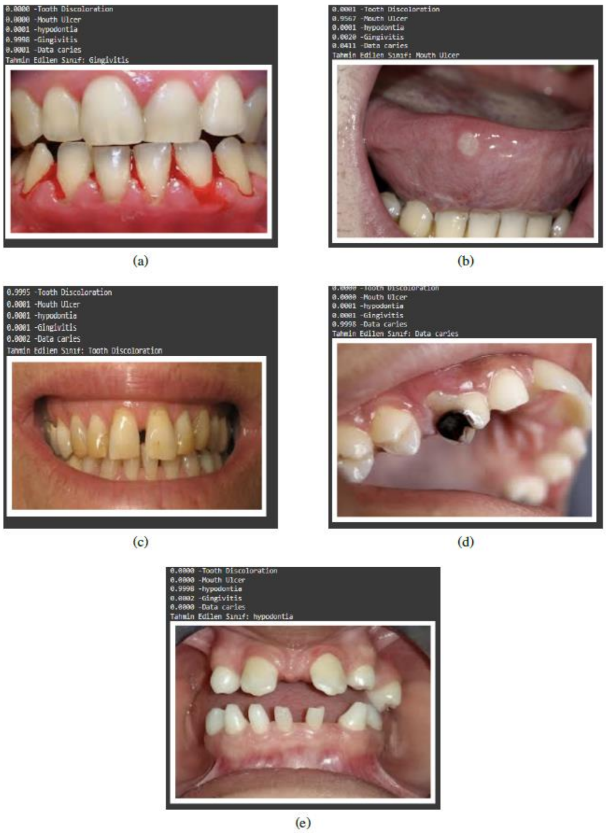


Figure 4. ResNet50 model results for dental diseases: (a) Gingivitis, (b) Mouth Ulcer, (c) Tooth Discoloration, (d) Caries, (e) Hypodontia.

The confusion matrix provides a detailed breakdown of the model's performance across all classes, highlighting both its strengths and areas for improvement. A detailed overview of the model's performance across all classes is provided in Figure 5.

The matrix reveals that the ResNet50 model achieves near-perfect classification for most classes, with only minor misclassifications observed in certain categories. For instance, Tooth Discoloration and Mouth Ulcer demonstrate flawless performance, as all instances are correctly classified without any errors. Similarly, Dental Caries and Gingivitis exhibit high accuracy, with only a few instances misclassified. However, Hypodontia shows slightly more confusion, particularly with Gingivitis, where five instances are incorrectly classified. This suggests that these two classes may share overlapping visual features, making them challenging to distinguish in some cases. Despite these minor errors, the overall performance remains robust. These results confirm the model's reliability in detecting dental diseases with high precision and accuracy, while also pointing to specific areas where further refinement could enhance performance.

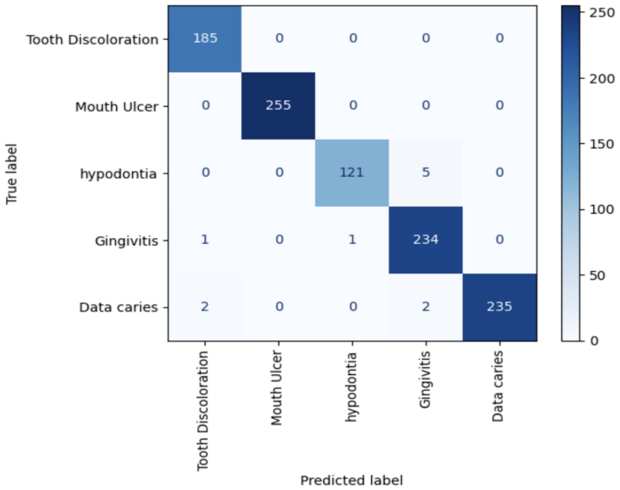


Figure 5. ResNet50 model's confusion matrix.

Finally, we compared the performance of ResNet50 with some AI-based models from the literature (Mask R-CNN, ResNet34, MobileNetV3, Attention U-Net-VGG16). Table 4 summarizes the comparison results of these models. The comparison in this table highlights the superior performance of the ResNet50 model proposed in this study, achieving an impressive accuracy of 99.00% for detecting dental diseases such as Tooth Discoloration, Mouth Ulcer, Hypodontia, Gingivitis, and Caries. This result significantly outperforms existing AI-based approaches, including those using Transfer Learning with MobileNetV3-Small (72.73%), Attention U-Net-VGG16 (81.66%), Transfer Learning with ResNet34 (81.82%), and Mask R-CNN (90.00%).

Table 4. Comparison of AI-based dental models.

Author(s)	Year	Model	Detected mouth diseases	Accuracy (%)
Garg et al. [34]	2023	Transfer learning MobileNetV3-Small	Calculus and Inflammation	72.73
Malaviya, P. [35]	2024	Attention U-Net-VGG16	Tooth Discoloration, Mouth Ulcer, Hypodontia, Gingivitis, Caries, Calculus	81.66
Garg et al. [34]	2023	Transfer learning ResNet34	Calculus and Inflammation	81.82
Liu et al. [33]	2019	Mask R-CNN	Decayed tooth, dental plaque, urosis, and periodontal disease	90.00
This Study	2025	ResNet50	Tooth Discoloration, Mouth Ulcer, Hypodontia, Gingivitis, Caries	99.00

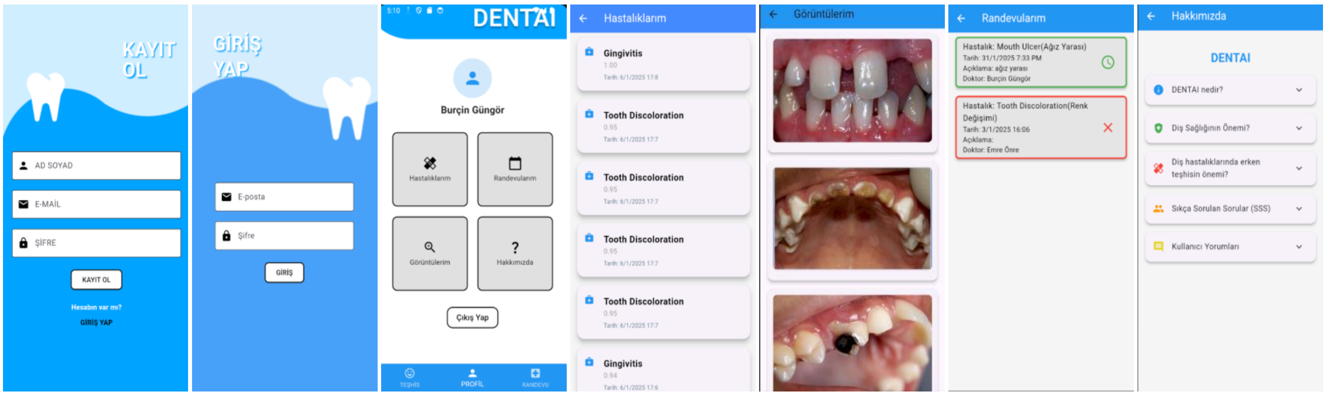
4.2. Model Performance in Real-World Scenarios

The AI-powered mobile application (DentAI) was developed to provide users with a practical and accessible tool for early detection of dental diseases using intraoral images. The application integrates the ResNet50 model to analyze user-uploaded images and deliver diagnostic feedback in real-time. This section evaluates the performance of the model within the mobile application, highlighting its strengths, limitations, and overall usability in real-world scenarios.

This mobile application consists of three main pages designed to streamline the user experience:

1. User profile page: After registration and login, users can access their personal information, historical data, and past diagnoses. This page also allows users to view previous disease records, images, and appointment details.
2. Disease diagnosis page: Users can upload intraoral images through this page to receive automated diagnostic feedback. The application processes the image using the ResNet50 model and provides predictions for five dental conditions: Tooth Discoloration, Mouth Ulcer, Hypodontia, Gingivitis, and Caries.
3. Appointment scheduling: Based on the diagnostic results, users can schedule appointments with dental specialists. This feature enhances the application's utility by bridging the gap between early detection and professional care.

The application was developed using Flutter, ensuring cross-platform compatibility for both Android and iOS devices. Backend functionalities, such as user authentication, data storage, and notifications, were implemented using Firebase, providing a secure and scalable infrastructure. The DentAI mobile application interface is illustrated in Figure 6, showcasing key screens such as registration, login, disease detection, and appointment scheduling. These screenshots provide an overview of the user-friendly design and functionality of the app.



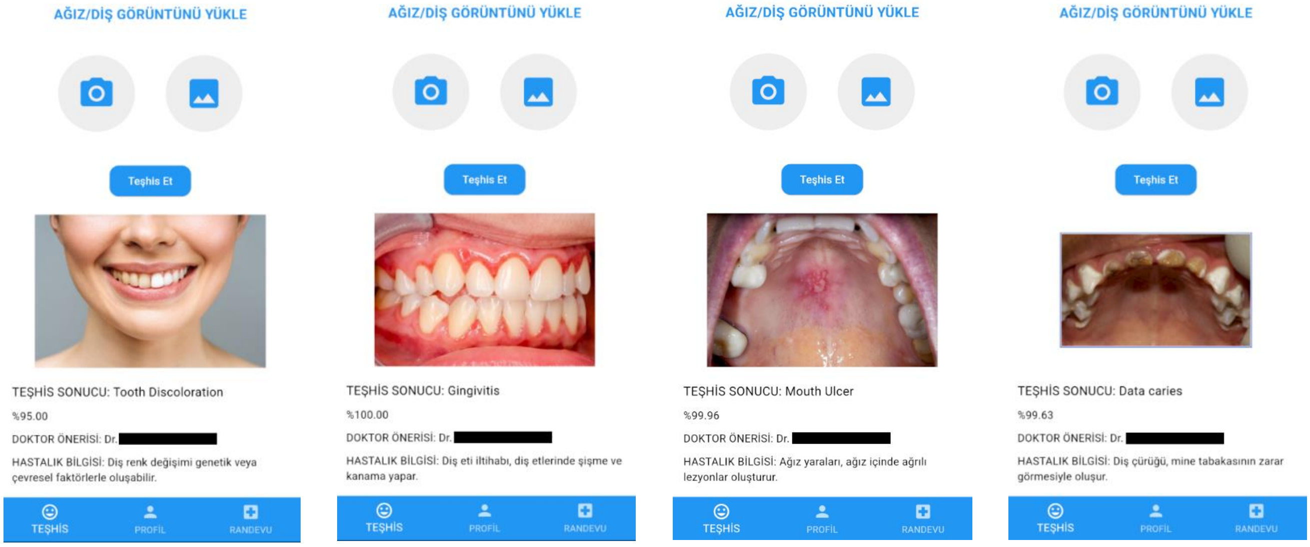
(a) (b) (c) (d) (e) (f) (g)

Figure 6. Screenshots of the DentAI mobile application interface: (a) Registration screen, (b) Login screen, (c) Home screen, (d) Disease detection screen, (e) Dental image history screen, (f) Appointment scheduling screen, (g) Settings screen.

The screenshots collectively demonstrate the seamless integration of AI-driven diagnostics within a mobile application framework. Each screen is designed to provide an intuitive user experience, ensuring that individuals can easily navigate through the app to detect dental diseases, review their health records, and seek professional care when necessary. The DentAI application empowers users with accessible, real-time dental evaluations while supporting dental professionals in prioritizing patient care based on objective findings.

The performance of the ResNet50 model was tested extensively within the DentAI application. Figure 7 illustrates examples of correct diagnoses made by this AI model. This figure illustrates four successful diagnostic outcomes achieved by the DentAI mobile application, showcasing its ability to accurately identify various dental conditions from intraoral images. Each example demonstrates the app's performance in detecting distinct oral diseases.

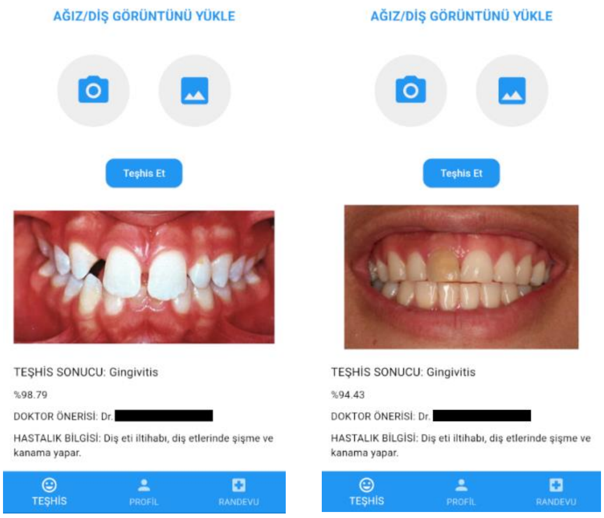
These examples highlight the model's reliability and precision in real-world scenarios, providing users with accurate diagnostic feedback for early intervention and treatment planning. The model's current single-diagnosis output may occasionally yield incomplete results when analyzing cases with multiple concurrent conditions, as demonstrated in Figure 8a which shows a patient presenting with both Hypodontia and Gingivitis.



(a) (b) (c) (d)

Figure 7. Examples of correct diagnoses in the DentAI mobile application: (a) Tooth Discoloration, (b) Gingivitis, (c) Mouth Ulcer, (d) Caries.

Additionally, rare diagnostic inaccuracies can occur due to either inherent model limitations or insufficient image clarity, exemplified in Figure 8b where ambiguous visual features led to suboptimal interpretation. These cases, while uncommon, highlight important considerations for clinical implementation and suggest valuable directions for model refinement.



(a) (b)

Figure 8. Examples of incorrect diagnoses in the DentAI mobile application.

4.3. Discussion of Findings

The findings of this study demonstrate the robust performance of the ResNet50 model in detecting dental diseases through intraoral images, highlighting its potential as a reliable diagnostic tool in both clinical and mobile health applications. The results, supported by high accuracy (99.00%), precision, recall, and F1-Score metrics across all classes, underscore the effectiveness of deep learning techniques in addressing complex medical image analysis tasks.

The ResNet50 model achieved exceptional performance on the test dataset, with minimal discrepancies between training and validation metrics. This indicates that the model successfully avoided overfitting, a common challenge in deep learning applications. The early stopping technique played a critical role in optimizing the training process, terminating training at epoch 15 and ensuring that the model maintained generalization capabilities. The confusion matrix further validates the model's reliability, with near-perfect classification rates for most disease categories, including Tooth Discoloration, Mouth Ulcer, and Dental Caries. However, minor challenges were observed in distinguishing between Hypodontia and Gingivitis, particularly in cases where multiple conditions coexisted within a single image. These findings align with prior studies, which emphasize the importance of addressing overlapping visual features in medical imaging datasets.

When compared to existing studies in the field, the ResNet50 model developed in this study outperforms many state-of-the-art approaches. For example, while models like MobileNetV2 and InceptionV3 achieved accuracies of 86.7% and 84.50%, respectively [11], the ResNet50 model achieved an impressive accuracy of 99.00%. Similarly, the Precision, Recall, and F1-Score values reported in this study surpass those obtained by other architectures, such as EfficientNetB0 and Xception, particularly in terms of balanced performance across all classes. These results validate the suitability of ResNet50 for medical image analysis tasks, particularly in the context of dental disease detection.

One of the key strengths of the proposed system lies in its ability to deliver accurate and timely diagnostic feedback through the DentAI mobile application. By integrating advanced AI-driven diagnostics with user-friendly functionalities such as appointment scheduling and historical data tracking, the application bridges the gap between early detection and professional care. The high macro average and weighted average scores (both 0.99) confirm that the model performs consistently across all classes, addressing potential class imbalances in the dataset. Furthermore, the use of pre-trained weights from ImageNet facilitated transfer learning, enabling the model to adapt efficiently to the specific characteristics of the Oral Diseases dataset. This approach not only reduced computational costs but also enhanced the overall performance of the model.

5. Conclusions

This study presents the development of an AI-powered mobile application, DentAI, designed to detect common dental diseases through intraoral images captured by users. The system leverages the ResNet50 deep learning model to analyze uploaded images and provide automated diagnostic feedback for conditions such as Tooth Discoloration, Mouth Ulcer, Hypodontia, Gingivitis, and Dental Caries. The application also integrates practical features such as user registration, historical data tracking, and appointment scheduling with dental professionals. The ResNet50 model demonstrated exceptional performance, achieving an accuracy of 99.00% on the test dataset, with balanced precision, recall, and F1-score metrics across all classes. These results highlight the potential of AI-driven tools in enhancing early detection, improving patient outcomes, and optimizing oral healthcare delivery.

Despite its high accuracy and robust performance, the proposed system has certain limitations that warrant attention. First, the current dataset includes only five disease classes, which may restrict the model's applicability to a broader range of oral conditions. Additionally, the model occasionally struggles with images containing multiple diseases, leading to incomplete or incorrect diagnoses. This limitation is particularly evident in cases where overlapping visual features or poor image quality obscure critical details. Furthermore, the reliance on intraoral images alone may not capture the full complexity of certain dental conditions, which often require additional clinical context or metadata for accurate diagnosis. Addressing these challenges will be essential to ensure the system's reliability and versatility in real-world scenarios.

Future research should focus on expanding the diversity and size of the training dataset to include a wider variety of dental conditions and edge cases. Incorporating multi-modal data, such as patient-reported symptoms, clinical history, or metadata, could provide additional context for diagnosis, particularly in complex cases. Additionally, exploring alternative architectures, such as ensemble models or hybrid networks, may further optimize accuracy and robustness. Another promising direction is the integration of real-time feedback mechanisms within the mobile application. For instance, users could receive guidance on capturing higher-quality intraoral images, ensuring more reliable predictions. Furthermore, incorporating a user feedback loop where individuals can report incorrect diagnoses and upload corrected labels would enable continuous improvement of the model. Conducting large-scale clinical trials would help validate the system's effectiveness in diverse settings and ensure compliance with regulatory standards, paving the way for broader adoption in clinical practice.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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