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Deep Learning-based Cavity Detection in Diverse Intraoral Images: A Web-based Tool for Accessible Dental Care

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Abstract

Dental cavities represent a widespread oral health issue on a global scale, impacting individuals across all age groups. The conventional approach to detecting cavities involves a visual examination by dentists, which is not only time-consuming but also subjective. Current methods for dental cavity detection heavily rely on subjective visual inspections, which may overlook early or concealed cavities. In this research paper, we present CatchCavity, a web application tool that utilizes deep learning for cavity detection in teeth. The diagnostic tool enables users to upload dental images, facilitating the assessment of dental cavity status. Furthermore, the web application functions as an online dental diagnostic service, providing the capability to securely store patients' dental records and information in a dedicated database. The system is trained on a dataset of annotated images and employs a convolutional neural network (CNN) architecture for accurate cavity detection. We evaluate the system's performance using metrics such as accuracy and loss. Our results showcase that the proposed system attains a high level of accuracy and efficiency in detecting dental cavities, achieving an overall accuracy of 98.7%. Additionally, our system surpasses traditional cavity detection methods, highlighting the possibility of deep learning approaches to enhance oral health outcomes.

Keywords: Oral Health; Cavity Detection;Web Application Tool; CNN(Convolutional Neural Networks); Deep Learning;

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1. Introduction

The landscape of oral health faces a persistent challenge in the form of dental caries, commonly known as cavities, affecting individuals of all age groups. These manifestations of permanent damage on the tooth's hard surface can evolve into small holes or openings, underscoring the critical need for timely detection and treatment. Conventional methods, reliant on visual inspection, may lack precision, potentially overlooking early or hidden cavities. Consequently, a pressing demand exists for more accurate and effective detection methods to prevent further tooth decay and minimize the necessity for invasive dental procedures.

In recent years, the advent of deep learning models has demonstrated promising results in various medical imaging tasks, including the identification of dental caries. Deep learning proves particularly relevant in its ability to analyze visual data, capturing nuances that may elude human observation alone.Deep learning and Convolutional Neural Networks (CNNs) are employed for cavity detection in intraoral images due to their proficiency in learning complex hierarchical features. intraoral images pose challenges with intricate patterns, making traditional methods less effective. CNNs, with their automatic feature learning through convolutional layers, excel in capturing nuanced details indicative of dental issues like cavities. The depth of neural networks allows for discerning subtle distinctions, making them ideal for identifying early signs of cavities. Their adaptability and generalization capabilities across diverse datasets further enhance their effectiveness in various dental imaging scenarios. However, a research gap persists in the application of deep learning models for detecting dental caries in color images taken with mobile cameras.

Existing studies predominantly focus on grayscale images from intraoral cameras or X-ray images, potentially failing to authentically represent the color and texture of teeth. Moreover, these images may not be as readily available as those captured by mobile cameras. Furthermore, limited research explores the efficacy of different deep learning models, such as ShuffleNet, MobileNet, VGG, NasNet, and ResNet, specifically for dental caries detection.

To address these gaps, this paper introduces a web-based application utilizing deep learning models for the detection of dental caries in color images captured by mobile cameras, as depicted in Fig. 1. The proposed system employs advanced deep learning techniques and segmentation for the accurate identification of dental caries. Additionally, it evaluates the performance of various deep learning models to identify the most effective one for this task. The system not only focuses on accurate detection but also provides users with valuable information, like stores user information during each check to show the comparisons and also shows nearest dental hospitals using location.

Key contributions of this research include:

1. Integrated Oral Health Identification: Streamlining the identification of various oral health concerns by analyzing photographs of an individual's mouth or teeth.
2. Teeth Categorization: Efficient identification of various oral health concerns through the analysis of photographs of an individual's mouth or teeth.
3. Development of Feature Set: Formulating a feature set through the training of various machine learning algorithms, enabling the identification of dental illnesses through the analysis of patterns in dental diseases.
4. Comprehensive Web Application: Developing a comprehensive online application that utilizes deep learning capabilities for effective evaluation of oral health, illustrating how technology can enhance healthcare accessibility and empower individuals to actively manage their dental well-being.

Finally, this paper aims to contribute to the field of dental caries detection by developing a comprehensive web-based application that utilizes deep learning models for the accurate detection of dental caries in color images captured by mobile cameras. The findings of this research will enhance the accessibility and efficiency of dental caries detection, particularly for individuals without access to specialized intraoral cameras or X-ray machines. In this study, we are utilizing advanced image classification techniques to identify dental cavities. The images, obtained from a diverse dataset, are processed through our classification model, which distinguishes between images with cavities and those without. Figure 1 encapsulates the model's outcomes, visually displaying its ability to categorize each image as 'Cavity' or 'No Cavity.' This binary classification holds significant promise for early cavity detection, a crucial aspect of preventive dental care. As we delve into subsequent sections, we will elaborate on the methodology and discuss the potential impact of our findings on improving dental health outcomes.

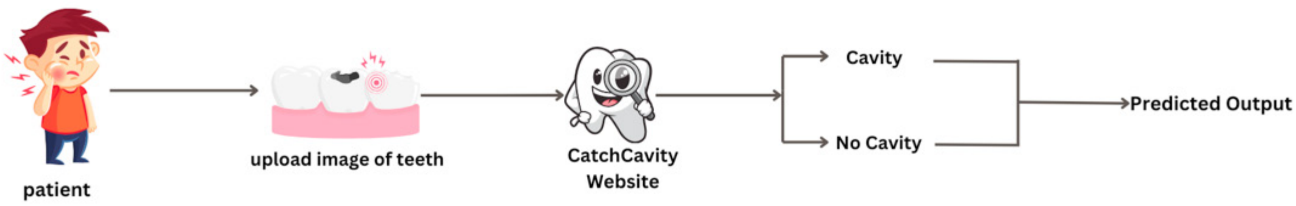

Fig. 1: CatchCavity: Overview of Dental Cavity Detection System

2. Related Work

Numerous studies have been conducted to forecast dental disorders and categorize dental cavities using machine learning (ML) and deep learning (DL) approaches. Apurva et al. (2020) introduced a Convolutional Neural Network (CNN) for dental cavity classification. Their model, consisting of ten layers, was trained on a set of 74 dental images. The CNN-based Sequential model incorporated convolutional and pooling layers, dropout layers for regularization, and dense layers with 'relu' and 'sigmoid' activation functions. Post-tuning, the model achieved a notable accuracy of 71.43% on a Kaggle-derived dataset, with the potential for increased accuracy through dataset expansion. The study envisions integrating this technology into a mobile application for swift cavity status assessments through dental image capture [1]. Hafeez et al. (2022) concentrated on dental cavity classification via a CNN. Their research involved formulating and training a CNN model using an extensive dataset of dental images, demonstrating effective classification performance and offering valuable insights into dental cavity detection [2].

Similarly, Prajapati et al. (2017) conducted a study on deep transfer learning for dental disease image detection. Using a Convolutional Neural Network and transfer learning techniques, they achieved an 88.46% detection accuracy with a small dataset of 251 RVG x-ray images, showcasing the potential of accurate disease detection through deep learning [3]. Kang et al. (2022) developed personalized machine-learning models for predicting dental caries based on patient-specific features, contributing to the advancement of personalized healthcare settings [4]. Goswami et al. (2021) proposed an automated system for oral cancer and dental caries detection using CNNs, showcasing the efficacy of CNNs in early diagnosis [5]. Bhattacharjee et al. (2022) demonstrated a system for identifying caries in dental images, emphasizing the complexity of dental caries detection [6]. Lee et al. (2018) evaluated deep CNNs using radiographs, achieving an 82% accuracy for premolars and molars [7]. Radha et al. (2023) explored diverse ML methods for dental caries identification, leveraging advanced computational techniques to enhance oral healthcare practices [8]. Duong et al. (2021) developed a smartphone-based ML system for identifying dental caries on teeth surfaces [9].

3. Dataset

The dataset is taken from Kaggle platform which consists large number of datsets.Kaggle dataset is organized into two main folders, namely train and test, containing images of teeth categorized into cavity and non-cavity classes. Initially, the dataset comprised a modest total of 74 images, with 60 images allocated to the train folder and 14 images to the test folder. In the train folder, there were 45 cavity images and 15 non-cavity images, while the test folder had 10 cavity images and 4 non-cavity images. Recognizing the potential limitations of this small dataset and the associated risk of overfitting, efforts were made to acquire additional data.

To address the data scarcity issue, data augmentation techniques were employed, leveraging the Keras library in conjunction with the Augmentor pipeline. A series of random transformations, including zooming, rotation, horizontal and vertical flipping, and adjustments to brightness, were systematically applied to the images. This augmentation process significantly expanded the dataset to a total of 454 images. To clarify the distribution within each folder post-

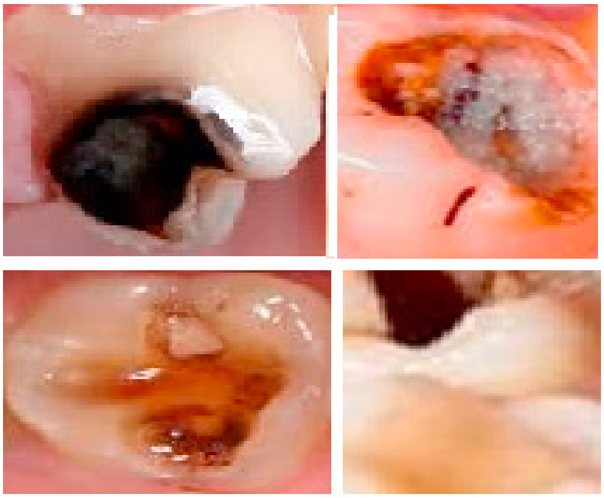

Fig. 2: Sample set of Cavity intraoral images in dataset

Fig. 3: Sample set of Non-Cavity intraoral images in dataset

augmentation, the train folder now accommodates 375 images, consisting of 225 cavity and 150 non-cavity images, and the test folder comprises a total of 79 images, with 45 cavity and 34 non-cavity images.

This augmented dataset, now with a more extensive and well-distributed image count across different classes and folders, serves as a valuable resource for computer vision projects, Sample images illustrating teeth with cavities Fig 2 and healthy teeth Fig 3 . Notable observations include clear distinctions in dental conditions, aiding in visual identification.

4. Proposed Model

The proposed approach involves developing a web application that utilizes a deep learning model to analyze dental images and to identify if dental caries are present or not. The application incorporates user authentication, image preprocessing, deep learning-based cavity detection, location-based dental facility recommendations, and user report generation. The first phase, data collection and diversity, emphasizes the critical need for a varied dataset. Gathering diverse dental images, depicting different facets of dental health, both with and without cavities, contributes to the creation of a comprehensive dataset. This diversity is crucial for training a model capable of generalizing well across various real-world scenarios.Moving to data cleaning and preprocessing, the focus is on ensuring the consistency of the dataset. By removing errors and standardizing the format of images, this stage aims to enhance model robustness. Consistency in data format facilitates seamless processing and reduces variability during the training phase. Following this, data augmentation techniques come into play, aiming to enhance dataset variability. Techniques like rotating and flipping are applied to expose the model to a broad range of variations in dental images. This ensures the model's adaptability to different perspectives and orientations, contributing to improved performance.Labeling, a critical step in supervised learning, involves categorizing each image as either having a cavity or not. This forms the foundation for training the model using labeled examples, enabling it to make accurate predictions on unseen data. The combination of these procedures in data collection, cleaning, augmentation, and labeling collectively enhances the model's ability to generalize and accurately identify dental caries across diverse scenarios.

In this paper, different CNN architectures are used to detect dental caries, including ResNet-50, VGG16, MobileNet, and ShuffleNet. ResNet-50 is a widely used deep learning model for image-related tasks, consisting of 50 layers with skip connections to address the challenge of training very deep networks. The model uses residual blocks

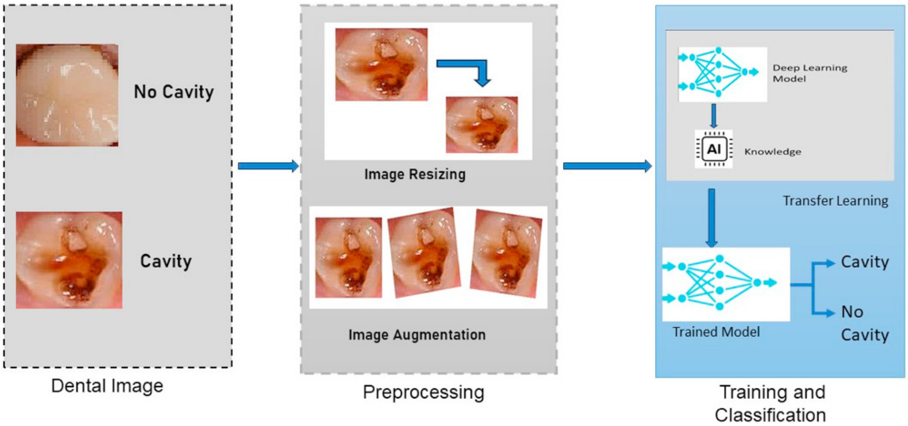

Fig. 4: Proposed Methodology Workflow

with shortcut connections to enable the learning of residual functions. VGG is a widely used deep learning architecture known for its deep structure with multiple convolutional layers and max pooling. VGG can capture intricate image features by using small filters. MobileNet is highly efficient in terms of computation and memory, using depth-wise separable convolutions to separate convolution filters into two groups and combine the output. ShuffleNet is highly efficient in terms of computation and memory, utilizing group convolutions and channel shuffling. We import pre-trained models of ResNet-50, VGG16, and MobileNet from Keras libraries and customize them for the binary classification task of caries detection by modifying the last few layers. We add dense layers and regularization to reduce overfitting. The trained models are evaluated on an independent testing set to assess their performance in dental caries detection. The models are then deployed to a suitable application for dental caries detection and tested on new, unseen dental images to assess real-world performance. The web application, built upon the Flask framework, provides a secure user authentication system with user registration and login functionality. User details, including username, password, full name, date of birth, and mobile number, are safely stored in a MySQL database in the 'userdetails' table. Furthermore, the application maintains a 'report' table to store information such as user ID, cavity detection status, confidence score, test date, and test time. This table allows users to monitor the progress of their previous image uploads. The login system is facilitated by session keys, ensuring that users can only access and view the results pertaining to their own data during the session. Upon successful login, the application utilizes routing to guide the user through the workflow. Initially, users are redirected to the login page. Once authenticated, they are prompted to upload an image of their teeth.

Regardless of the image size, the web application employs preprocessing techniques to ensure compatibility with the deployed machine learning model. In dental cavity detection, image preprocessing is crucial for better analysis. This involves resizing images for consistency, converting them to grayscale for efficiency, and using techniques like histogram equalization to improve contrast. To address imperfections, noise reduction methods are applied, and augmentations like rotation and flipping diversify the dataset for improved generalization. Cropping focuses on the tooth area, and data whitening normalizes pixel values. These steps collectively optimize dental images for accurate cavity detection, improving diagnostic accuracy.

This model is designed to detect cavities, and after the successful preprocessing and image upload, the application displays the results .Fig 4.Illustrate outlining the step-by-step workflow of the proposed methodology. Key observations highlight the systematic approach, guiding users through each crucial stage of the process. Specifically, it informs the user whether they have cavities or not, accompanied by a confidence score indicating the model's level of certainty. We customize the models by modifying the last few layers to adapt them to the binary classification task of caries detection. We modified these models by adding some dense layers and also by adding regularization to reduce overfitting.

The classification is achieved through a process where the model is trained to distinguish between images containing dental cavities and those without. A dataset of dental images, annotated with labels indicating the presence or absence of cavities, is used for training. Convolutional Neural Networks (CNNs) are commonly employed due to their effectiveness in image-related tasks. The model learns hierarchical features and patterns within the images during training. The final layer typically employs a sigmoid activation function, producing a probability score between 0 and 1, representing the likelihood of a cavity's presence. During training, the model's parameters are optimized using a loss function such as Binary Cross-Entropy, which quantifies the disparity between predicted and actual labels. Once trained, the model can classify new dental images by predicting the probability of cavity presence, aiding in automated and efficient cavity detection in dental diagnostics.

In order to enhance user experience and accessibility, the web application includes a feature where users, upon receiving a cavity diagnosis, can input their current location. This is facilitated using JavaScript's prompt function, which prompts the user to enter their location. Upon input, the code dynamically generates a Google Maps URL by combining the user-entered location with predefined values such as ”best,” ”dental,” and ”hospital.” This URL is then used to redirect the user's browser. Two methods, window.location.href and window.location.replace, are leveraged for this purpose. The former changes the current page's URL and adds it to the browser's history, allowing users to navigate back to the application. The latter, window.location.replace, replaces the current page's URL without recording it in the browser's history. This feature seamlessly integrates healthcare guidance with location-based services, enabling users to explore and locate the best dental hospitals in their vicinity.

The entire process, from user login to result display, is seamlessly orchestrated through Flask's routing mechanism. Flask, a Python web framework, manages the different routes of the application. This includes handling user authentication, processing location inputs, generating PDF reports, and displaying relevant information on different pages. The integration of Flask, coupled with MySQL for database operations and deep learning models for dental health assessment, showcases a cohesive approach in technology stack utilization. This not only enhances the user experience but also demonstrates the potential for technology to empower users to actively manage and track their dental health over time. The implementation aligns with the broader goal of utilizing technology to enhance healthcare applications and encourage proactive measures for well-being.

5. Experimental Results and Discussion

The model used is built on the NASNetMobile architecture and is optimized for picture classification. The implementation is done in Python 3.9 with Google Colab, with the dataset divided into 80% for training and 20% for testing. A pre-trained NASNetMobile base model is followed by extra layers for fine-tuning and categorization. The pre-trained weights from the ImageNet dataset are used to initialize the base model. A flatten layer, two dense layers with 512 and 256 neurons, ReLU activation functions, and L2 regularisation with a coefficient of 0.001 for both kernel and bias are all part of the design. To prevent overfitting, dropout layers with a rate of 0.2 are incorporated. For classification, the final dense layer consists of two neurons with softmax activation.

Model compilation involves an RMSprop optimizer with a learning rate of 0.0001. Categorical cross-entropy loss is employed as the loss function, and accuracy is selected as the evaluation metric. Training spans 15 epochs using train and validation generators. The training data is fed through the train generator, while the validation data is supplied via the validation generator. The model is trained to minimize loss and enhance the accuracy of the training data. Notably, during training, an uptick in validation loss is observed after 25 epochs, leading to a decline in validation accuracy. To avert overfitting, the epoch count is capped at 25. Post-training, the model undergoes testing with two distinct optimizers: RMSprop and Adam's propagation. Results reveal that Adam's propagation outperforms RMSprop in terms of accuracy and loss. Consequently, Adam's propagation is chosen to optimize the proposed model. Accuracy and loss serve as the evaluation metrics, offering insights into the model's image classification accuracy and the extent of prediction errors.

The increase in accuracy with an increase of epochs is visually shown in Fig.5 and the Decrease of Loss with an increase of epochs is visually shown in Fig.6.

The performance of the model is evaluated using accuracy and loss. The accuracy of deep learning models in detecting dental cavities can be defined as a measure of how correct the model's predictions are. It is calculated as the ratio of correctly identified dental cavities (true positives) and non-cavities (true negatives) to the total number of images.

As dental cavity detection is a binary classification problem, binary cross-entropy loss function is employed to compute the model's loss. It measures the dissimilarity between the predicted probabilities and the true labels. In the context of dental cavity detection.The Binary Cross-Entropy Loss is then defined as:

$$\text{Log loss} = \frac{1}{N} \sum_{i=1}^{N} -\left(y_i * \log(p_i) + (1-y_i) * \log(1-p_i)\right)$$

Fig. 5: Binary Cross Entropy Loss function

N is the number of samples in the batch. y_i is the ground truth label for the i-th sample (1 for cavity, 0 for no cavity). p_i is the predicted probability of having a cavity for the i-th sample. The accuracy and loss of ResNet50,MobileNet,ShuffleNet,VGG-16 and NasaNet are given in Table 1.

ResNet50 exhibits commendable accuracy during training, but its performance suffers from pronounced overfitting during testing, evident in higher loss values compared to other models.

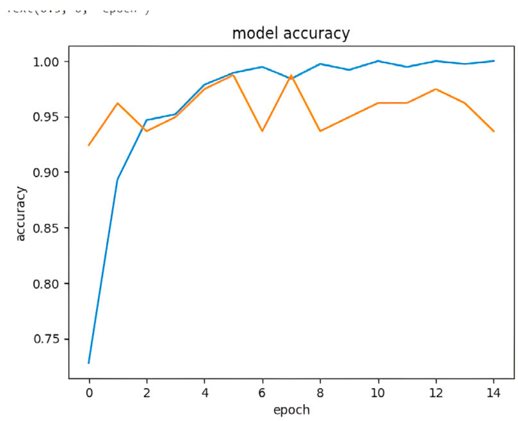

Fig. 6: Accuracy for VGG model on each epoch

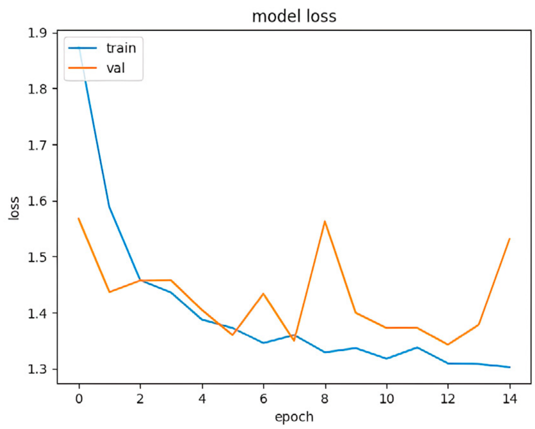

Fig. 7: Loss for VGG model on each epoch

In contrast, ShuffleNet and MobileNet stand out by showcasing the least loss among all models, suggesting their efficiency in minimizing overfitting. Notably, ShuffleNet, NasaNet, and Vgg16 demonstrate high accuracy's .Accuracy (Fig 5) and loss (Fig 6) trends over epochs for the VGG model, highlighting performance variations during training. and, indicating robust decision-making and predictive capabilities with respect to the dataset. Of particular significance is the superior performance of ShuffleNet, which combines substantial accuracy with minimal loss, making it a promising candidate for cavity detection in images. The utilization of ShuffleNet in cavity detection yields compelling outcomes.

These findings underscore the importance of selecting an appropriate deep-learning model for the specific task at hand, considering both training and testing performance metrics. The detailed evaluation presented here guides the choice of ShuffleNet for cavity detection, showcasing its potential to enhance diagnostic accuracy and mitigate overfitting challenges .Accuracy (Fig 7) and loss (Fig 8) progression over epochs for the ShuffleNet model, offering insights into training dynamics.

The findings from our study demonstrate that the Canny Edge-CNN model emerged as the top-performing model, achieving an impressive accuracy of 70.64% on the test data, as outlined in the "Forecasting Teeth Cavities By Convolutional Neural Network" paper. However, it is noteworthy that our Shufflenet model surpassed these results, achieving

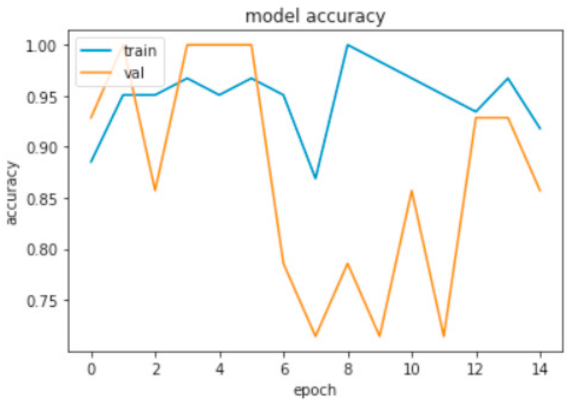

Fig. 8: Accuracy for ShuffleNet model on each epoch

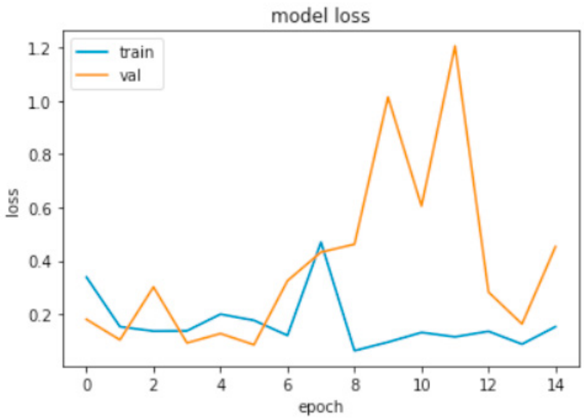

Fig. 9: Loss for ShuffleNet model on each epoch

Model	Train Accuracy	Train Loss	Test Accuracy	Train Loss
ResNet50	0.9467	1.5288	0.5696	5.8374
ShuffleNet	0.9180	0.1521	0.8571	0.4531
MobileNet	0.8693	0.3261	0.9114	0.2006
NasaNet	0.9947	0.8916	0.9241	0.9648
Vgg-16	0.9973	1.3166	0.9873	1.3333

Table 1: Accuracy and Loss for each Model

an even higher accuracy rate of 85%. This substantial performance gap between the two models underscores the superior efficacy of our Shufflenet model in handling the given dental image dataset.

Furthermore, the comparison between the models highlights an intriguing pattern: the performance of our models, specifically designed and trained on intraoral images, significantly outperforms those trained on X-ray images. The notable disparity in accuracy between the Canny Edge-CNN and Shufflenet models further reinforces the conclusion that our approach, utilizing intraoral images as the primary dataset, is particularly effective in the context of forecasting teeth cavities. This insight could have broader implications for the field, suggesting that a dataset composed primarily of intraoral images may yield more accurate and reliable results in dental imaging applications compared to datasets based on X-ray images. Also ShuffleNet model gives higher accuracy than the Dental cavity Classification using Convolutional Neural Network paper which gives 71.43%. This gives the idea that ShuffleNet performs better than some existing methodologies. Further research and exploration in this direction could provide valuable insights into optimizing model performance for dental health applications.

To Enhance the efficiency and reliability of our project, which currently operates with a limited dataset, is closely tied to the augmentation and enrichment of our existing data pool. A larger and more diverse dataset serves as a reservoir of valuable information, empowering our model with a broader understanding of patterns and variations inherent in the data. With a richer dataset, the model can discern subtleties and nuances more effectively, contributing to heightened accuracy and reliability in its predictions. This approach not only bolsters the system's ability to generalize across different scenarios but also mitigates the risk of overfitting, a common challenge when dealing with constrained datasets. Therefore, investing in the expansion and enhancement of our dataset emerges as a pivotal strategy to significantly elevate the efficiency and reliability of our project, laying the foundation for more robust and dependable outcomes.

6. Conclusion

Our study unveils the transformative potential of deploying deep learning models in dental diagnostics, significantly elevating the accuracy of cavity detection. We meticulously trained five models—VGG16, ResNet50, NasaNet, ShuffleNet, and MobileNet—implementing advanced data augmentation techniques alongside optimized parameters. Leveraging the Adam optimizer with a 0.001 learning rate and a batch size of 32, we achieved a dual objective: minimizing loss while maximizing model accuracy.Our results demonstrate an impressive accuracy of 85% in detecting cavities within mobile camera images, a noteworthy feat considering the inherent challenges posed by the lower quality and susceptibility to noise and distortion in mobile images. The strategic implementation of data augmentation not only mitigated overfitting but also empowered us to train our models effectively with a more constrained dataset, a distinct advantage in resource-limited settings.Most deep learning methodologies rely on X-ray images, which are impractical for home use. Our approach utilizes images taken by mobile cameras, resulting in a lower initial accuracy due to limited data. However, the potential for significantly higher accuracy exists with the acquisition of more data. A more extensive dataset could propel our system to be a highly efficient cavity detection system for home use, overcoming the limitations associated with obtaining X-rays outside of professional settings.The implications of our findings extend beyond the immediate context, showcasing deep learning's potential to revolutionize dental diagnostics. As accuracy continues to ascend, the prospect of individuals conducting self-assessments gains prominence, potentially reducing dependence on frequent professional visits for preliminary evaluations.Future research endeavors stand to further amplify these outcomes. Exploring advanced methodologies, such as ensembling and transfer learning, holds promise for enhancing model performance and extending the applications of automated cavity detection. The envisioned automation could usher in a paradigm shift in dental healthcare, facilitating timely interventions and alleviating the burden on healthcare systems.

In conclusion, our work lays the foundation for a transformative shift in dental diagnostics, bringing highly efficient cavity detection to the convenience of homes. The potential for increased accuracy with a more extensive dataset opens avenues for widespread adoption, empowering individuals to actively manage their dental health. Future works will focus on expanding the dataset, exploring novel deep learning techniques, and refining the system for broader applications in home-based dental diagnostics.

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