SMART ORAL HEALTH GUARDIAN: REVOLUTIONIZING DENTAL CARE WITH DEEP LEARNING

[Document subtitle]

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Abstract

The realm of dentistry entails a vital role and responsibility of safeguarding oral health and preventing potential dental ailments. However, many people often overlook the need to maintain their dental well-being due to their bite and work schedules. As a result, one may develop a dental problem without their knowledge, which may escalate into a severe problem to treat. In line with this lifesaving need, we introduce this innovative concept that utilizes the dental selfies and machine learning advanced algorithms to achieve multiclassification of various oral conditions.

Our project intends to revolutionize proactive dental care in an affordable system and user-friendly. The integration of a toothbrush with a camera and sensors enables people to take dental selfies and real-time classification. The ultimate aim of this method is to aid users in early detection and solution to dental problems, promoting the right lead to timely preventive measures for good oral health. We can further confirm that after several trials using a broad range of the Convoluted Neural Network models which include VGG16, MobileNet, DenseNet, etc., the maximum achievable accuracy stood at 98%, which is an excellent result This implies that the model accurately evaluates oral health status based on dental selfies and indicates that this approach is a significant leap forward in the early detection of dental issues and a precise approach to proactive oral care.

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1. Introduction

Oral health is a big concern across the world, touching an impressive 3.5 billion people everywhere. It's a huge issue of great size. Among these folks, a shocking 2.3 billion have tooth decay in their adult teeth, making it the top health problem around the globe. This worrying fact is true in all places, goes beyond rich and poor gaps, and meets across different ways of life, showing how common tooth troubles are for everyone.

The idea that keeping our mouths healthy is key to our overall well-being has led to it being seen as very important. This idea comes from the thought that everyone has the right to good oral health, pointing out how crucial it is to have easy-to-reach and effective dental care to live well. Oral health is now seen as part of our total health, fitting with the World Health Organization's broader view of health that includes how well we get along in society. This bigger view shows that good oral health is vital for making our life better in many ways.

Oral health is profoundly ingrained in our daily lives. The ability to eat, speak, and smile depends on the condition of our mouth. A healthy mouth allows us to enjoy eating the right kind of foods, communicate well, and even express ourselves confidently through a smile. Apart from the basics, the status of oral health also determines our ability to contribute creativity and productivity to society. Our oral status has a high bearing in our relationships, both social and professional, as it touches on our ability to work well with others, whether colleagues, friends, or family. It, therefore, extends from the easiness of our own well-being to impact broadly on other people. Dentistry has in the recent past undergone tremendous changes with the aid of machine learning.

For oral disorders to be prevented from worsening and to have as little financial and health impact as possible, early detection is essential. Another area where machine learning is significantly improving oral healthcare is in treatment planning.

Moreover, by analyzing patient data, such as clinical records and medical histories, machine learning helps create personalized treatment regimens. These customized plans address the particular needs of every patient, leading to better treatment outcomes and higher levels of patient satisfaction.

2. Problem Definition

Negligence and the limitation of access to dental services are some of the reasons why many people do not know how important oral health is. Dental issues, for instance, are ignored by a lot of individuals until they become worse thereby leading to more serious complications as well as expensive treatments. We propose an innovative solution that completely solves this problem through leveraging dental selfies in combination with the most advanced machine learning algorithms for early identification and classification of various dental conditions like cavities and gum diseases among others based on seven major classes. This means that we have several categories into which these are grouped beyond just “Healthy” or “Unhealthy”. The main objective therefore is to create a tool that cost-effective and easily accessible thus helping users proactively determine their various dental challenges through multi-classification.

Existing Scenario:

The current scenario highlights a gap in proactive oral health care, emphasizing the need for an innovative solution. While traditional dental care relies on scheduled appointments, our project introduces a technologically advanced toothbrush incorporating a camera and sensors. This toothbrush aids in classifying dental selfies across seven distinct categories which are- **Calculus, Healthy, Data Caries, Gingivitis, Mouth Ulcer, Tooth Discoloration and Hypodontia** offering a comprehensive means of assessing oral conditions. The proposed solution aims to empower individuals to take control of their oral health with a user-friendly and technologically sophisticated approach.

Approach and Experimentation:

To ensure the accuracy of our multiclass classification solution, we conducted comprehensive experiments using various Convolutional Neural Network (CNN) models, including VGG16, **MobileNet**, DenseNet, and VGG19. Rigorous testing yielded a maximum accuracy rate of **98%**, demonstrating the effectiveness of our approach in evaluating a wide range of oral health conditions based on dental selfies.

Innovation and Impact:

Our project stands as an innovative stride towards democratizing oral health awareness. By seamlessly integrating technology into daily dental care routines, individuals can receive prompt feedback on their oral health status across multiple categories. The tool encourages timely preventive measures and treatment, ultimately contributing to enhanced overall oral well-being through a comprehensive multiclass classification system.

3. Background Survey

Several recent research studies investigating the use of machine learning (ML) algorithms in dental image analysis to improve the accuracy and efficiency of dental treatment have been conducted by Lee et al. (2018) (2018) no. Liu et al. (2019) introduced a smart dental health-IoT platform using deep learning and collected 12,600 clinical images for automated diagnosis of 7 dental diseases with an accuracy of up to 90%. Githa and others. (2020) developed a dental caries diagnosis system to achieve 97.1% accuracy using a neural network on intra-oral digital radiography images.

Also, egg imac et al. (2022) proposed an automatic tooth detection method based on periapical images, where a multi-input intensive CNN ensemble model obtained an impressive accuracy score of 99.13% Kayyum et al. (2023) introduced a semi-supervised learning method for detecting tooth decay, which shows performance improvement compared to standard self-monitoring learning methods Singh and Sehgal (2017) with modifications and classifiers used X-ray images for dental diagnosis, resulting in high accuracy and excellent predictive value Chen et al. (2019) and Navarro et al. (2019) used different ML methods to detect teeth and gums, which showed high accuracy and precision in dental image analysis. Patil and so on. (2019) proposed a caries detection method with 95% accuracy based on optimization algorithm of feature extraction in digital dental X-ray images.

Retrospective analysis reveals impressive accuracy in applying machine learning algorithms to dental image analysis, gum search, detection of oral health conditions, and overall dental condition a segmentation, which shows the changes that occur when dental practices are controlled by the combination of cutting-edge technologies such as dental modifiers and deep learning; Going forward, the outcome for individuals worldwide will be to enhance and extend existing knowledge by adding new techniques to tailor the accuracy and ability of dental imaging screening systems has been successful.

4. Proposed Methodology

4.1 Architecture

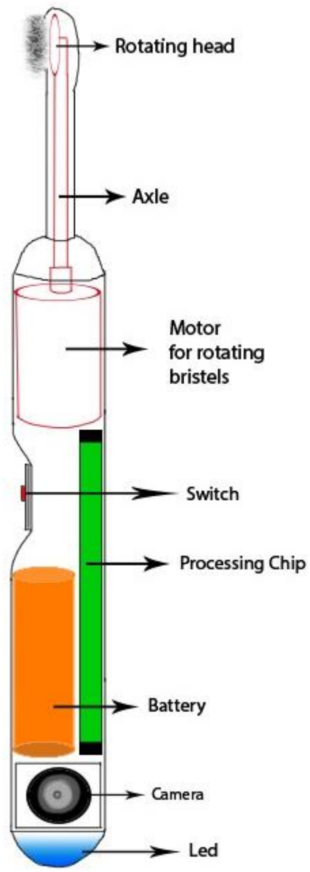

Figure 1. Design of Smart Toothbrush

Design and Description

Motor: It powers the rotation of the brush head, enabling effective cleaning.

Battery: It supplies power to the motor and the processor, ensuring consistent and reliable functionality for Smart brushing.

Processing Chip: The processing chip is the brain of the toothbrush. It incorporates essential sensors, such as the pH sensor and Bluetooth chip to measure the acidity of saliva and communicate data to the user's phone. Additionally, it incorporates a built-in timer and multiple vibration modes to ensure precise brushing time and enhance overall cleanliness. It also processes information for efficient toothbrush operation.

Camera: The camera is an innovative addition to the toothbrush, allowing users to capture dental selfies. It plays a vital role in the early detection of oral issues by providing clear images of the user's teeth for analysis and diagnosis.

LED Light: It enhances the uniformity of brightness within the oral cavity. Its primary function is to ensure optimal lighting conditions for capturing high-quality dental selfies.

A. Dataset collection and preparation

Our dataset consisted of **14,249** dental selfies, thoughtfully curated to maintain a balanced representation of all the 7 classes. This 8:1:1 ratio ensured that the model would not be biased towards any specific class. To enhance the dataset, the ImageDataGenerator technique was applied. This augmentation process involved applying transformations such as rotations, flips, and zooms to the images, creating a more diverse and robust dataset.

TABLE I
LABELS AND NUMBER OF IMAGES USED IN DATASET

Classes	**No. of Images**
Healthy Teeth	2596
Calculus	1296
Caries	2382
Gingivitis	2349
Hypodontia	1251
Mouth Ulcer	2541
Tooth Discoloration	1834

B. Dataset Splitting

To evaluate the performance of the classification model effectively, the dataset was divided into three subsets: **training, testing, and validation**. The training set (11395) was utilized to train the model on a large portion of the data, allowing it to learn the underlying patterns and features of dental conditions. The testing set (1422) was reserved for assessing the model's performance on unseen data, while the validation set (1432) was used to fine-tune hyperparameters and prevent overfitting.

C. Model Architecture

We conducted a binary classification task using four distinct pre-trained models: VGG 16, MobileNet, DenseNet, and VGG 19, all with weights initialized from the ImageNet.

1. VGG 16:

- Base Architecture: VGG 16 with ImageNet weights.
- Custom Layers: A few additional fully connected layers with appropriate activation functions.
- Output Layer: A single neuron with a sigmoid activation

2. MobileNet:

- Base Architecture: MobileNet with ImageNet weights.
- Custom Layers: A Global Average Pooling layer followed by a fully connected layer with appropriate activation functions.
- Output Layer: A single neuron with a sigmoid activation function for binary classification.

3. DenseNet:

- Base Architecture: DenseNet with ImageNet weights.
- Custom Layers: A Global Average Pooling layer followed by a fully connected layer with appropriate activation functions.
- Output Layer: A single neuron with a sigmoid activation function for binary classification.

4. VGG 19:

- Base Architecture: VGG 19 with ImageNet weights.
- Custom Layers: A few additional fully connected layers with appropriate activation functions.
- Output Layer: A single neuron with a sigmoid activation function for binary classification.

D. Model Compilation

We used binary cross-entropy as the loss function and employed adam optimizer for training.

E. Training and Validation

The models are trained using the training dataset for 36 epochs with a batch size of 4. Validation data is used to monitor the model’s performance during training and prevent overfitting.

4.2 Algorithm

Input

- Collect images of teeth for each of the 7 classes: Calculus, Healthy, Dental Caries, Gingivitis, Mouth Ulcer, Tooth Discoloration, and Hypodontia.

Preprocess the dataset:

- Split the dataset into training, validation, and test sets in ratio [7 : 1 : 2]

Build a Convolutional Neural Network(CNN) model for image classification:

- Create the CNN architecture with convolutional layers, max-pooling layers, and fully connected layers.
- Pre-trained weights from ImageNet is used as the base architecture and additional layers. • Compile the model with appropriate loss function (e.g., binary cross-entropy) and optimizer (e.g., Adam).

Train the model:

- Train the model using the training dataset.
- Use the validation dataset for early stopping to prevent overfitting.

Evaluate model performance:

- Evaluate the model's performance on the test dataset.
- Calculate accuracy, precision, recall, and AUC to evaluate multiclass classification quality.
- Do a comparative analysis based on other models' performance.
- MobileNet model outperforms compared to other CNN models on test dataset with respect to accuracy and correct predictions.

Output:

- Predicted multiclass classification of the input image into one of the 7 classes: Calculus, Healthy, Dental Caries, Gingivitis, Mouth Ulcer, Tooth Discoloration, or Hypodontia.

A. Our Process Flow

As the user brushes their teeth using a smart toothbrush, the process can be triggered. The toothbrush will have a camera or imaging sensor to take pictures of the user's teeth as they brush them. Preprocessing may be done to remove the noise and other information not related to the task of interest. In this analysis, the multiclass classification of dental conditions is then run. Therefore, if the probability score is greater than a threshold for a given condition, it will show that the user's teeth might have that condition. In this easy process, technology helps to give users insightful details of their oral health and to identify problems on time and thus work for better oral hygiene. It also motivates routine monitoring and consulting dentists whenever necessary, hence improving the overall management of oral care needs.

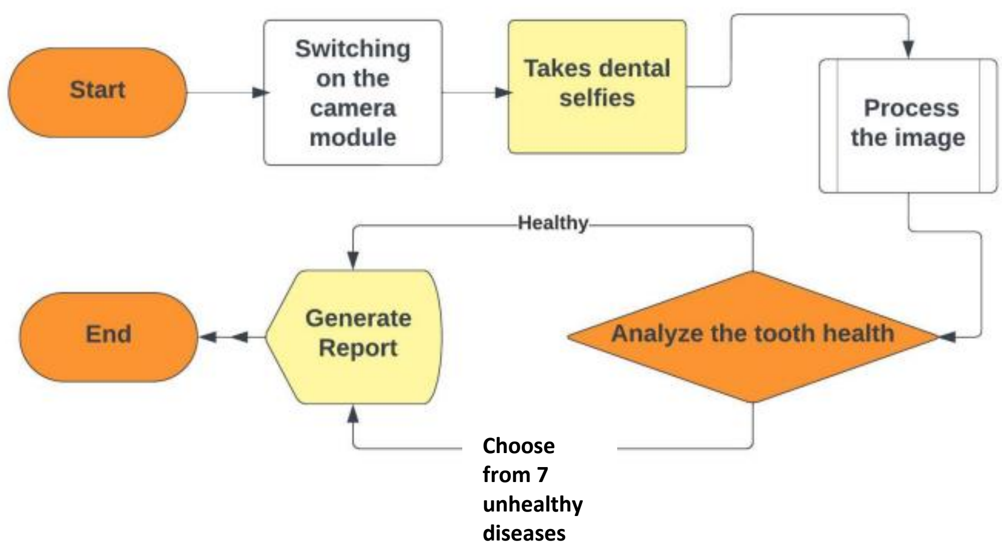

Fig 2: Process Flow

4.3 Source Code

```python
# Function to load and preprocess images
def load_and_preprocess_image(img_path, model_name, target_size=(224, 224)):
    img = image.load_img(img_path, target_size=target_size)
    img_array = image.img_to_array(img)
```

```python
    img_array = np.expand_dims(img_array, axis=0)

    if model_name == "DenseNet":
        img_array = densenet_preprocess(img_array)
    elif model_name == "MobileNet":
        img_array = mobilenet_preprocess(img_array)
    return img_array

# Function to extract the actual class from the file name
def extract_actual_class(filename):
    base_name = os.path.splitext(filename)[0]
    actual_class = base_name.split(' ')[0].split('.')[0]
    return actual_class

# Number of rows and columns for the plot
num_images = len(image_files)
num_cols = 2
num_rows = (num_images + num_cols - 1) // num_cols

# Plot images with predictions
fig, axes = plt.subplots(num_rows, num_cols, figsize=(20, num_rows * 10))

for ax, img_file in zip(axes.flat, image_files):
    # Load and preprocess the image
    img_path = os.path.join(image_folder, img_file)
    img_array_densenet = load_and_preprocess_image(img_path, "DenseNet")
    img_array_mobilenet = load_and_preprocess_image(img_path, "MobileNet")

    # Get model predictions
    pred_densenet = densenet_model.predict(img_array_densenet)
    pred_mobilenet = mobilenet_model.predict(img_array_mobilenet)

    # Get class indices and probabilities
    class_densenet = np.argmax(pred_densenet, axis=1)[0]
    class_mobilenet = np.argmax(pred_mobilenet, axis=1)[0]
    class_densenet_prob = pred_densenet[0][class_densenet]
    class_mobilenet_prob = pred_mobilenet[0][class_mobilenet]

    # Map class indices to class names
    class_densenet_name = class_names[class_densenet]
    class_mobilenet_name = class_names[class_mobilenet]

    # Extract the actual class from the file name
    actual_class = extract_actual_class(img_file)

    # Display the image
    img = image.load_img(img_path)
```

```python
    ax.imshow(img)
    ax.axis('off')
    ax.set_title(f"Truth: {actual_class}\nDenseNet: 
 ↪{class_densenet_name}\nMobileNet: {class_mobilenet_name} ", fontsize=12)

# Hide any unused subplots
for i in range(len(image_files), num_rows * num_cols):
    fig.delaxes(axes.flat[i])

plt.tight_layout()
plt.show()
```

Starting from pre-processing of the images to train the different CNN models we have come down to the final 2 models. Here, we demonstrate and evaluate their prediction on a set of images.

This piece of code aims at analyzing images in a specified folder with the pre-trained DenseNet and MobileNet for the image classification task. Firstly, images are loaded from a specified folder; secondly, pre-processing is done according to the requirement of the model being used, and after that, classes are predicted on the DenseNet and MobileNet models. The actual class of an image is extracted from the filename; the predicted classes with their probabilities are displayed along with the original image. In this snippet, it has been demonstrated how to leverage a pre-trained deep learning model to classify images and visualize the results to understand how the model will work on a given dataset.

5. Requirements Specifications

For this, the system needs an efficient hardware setup that can capture high-quality dental photos and processing them with state-of-the-art deep learning-based algorithms. In addition, modern software libraries in the software stack should also cover image processing, deep learning, and wireless communication to provide accurate disease detection and seamless interaction with mobile applications.

i) Software Requirements:

a) Python 3.10 or above.
b) Jupyter Notebook.
c) OpenCV 4.5.3 or above for image processing
d) TensorFlow 2.7.0 or above
e) Keras 2.7.0 or above libraries for deep learning

6. Output Analysis

6.1 Output

Fig 3: Truth VS Prediction

6.2 Analysis

According to our results, we conclude that the MobileNet model is the best for this image classification task. It achieved higher accuracy and good performance on an unseen test set, which is an indication that it generalizes to new data better.

On the other hand, while the DenseNet model did perform decently, it could not match the level of consistency with respect to prediction as that of MobileNet, which fell in line with the true labels. This is indicative of the fact that it's the MobileNet architecture that performs best over the particular dataset and problem.

That is why, in a nutshell, the model of MobileNet was chosen as the ultimate choice for this project in the classification of teeth images. Good performance in the 10 unseen test images was enough to give predictive capabilities with good accuracy for the model to predict classes of teeth images. The model can now be deployed for real-world use with confidence in its predictive capability.

7. Future Scope of the Project

Our current focus is on classifying seven dental situations into various categories using advanced system learning strategies to accurately identify them. We have a model ready for the Smart Oral Health Guardian device to implement the software, and we are currently working on integrating it with the hardware. Going forward, we plan to integrate generative AI to enhance our classification method by generating synthetic data for the seven categories. This integration will support our data shape, improve version generalization, and potentially utilize generative networks for real-data development.

Additionally, our future efforts include expanding the category system to encompass more oral diseases, refining existing categories, and incorporating modern object detection algorithms for greater accurate classification. We intend to revolutionize oral health evaluation by combining multiclass classification with generative AI. Through these efforts, we aim to make a significant impact on diagnostic equipment in the dental and medical communities, providing micro-complete processes to oral health assessment and advancing the field.

8. Conclusion

Our revolutionary toothbrush, which incorporates dental imaging and advanced machine learning, represents a significant step forward for early detection of oral health conditions. By providing easy guidelines for better understanding clients' oral health status, we aim to simplify diagnosis and encourage proactive oral care practices. We recognize the immense potential of our technology and are aware of the transformative impact that can be brought about by extending early disease diagnosis to improve oral health care practices.

We have tested our method using several Convolutional Neural Network (CNN) models, which have shown that our approach is robust and has achieved high accuracy rates of up to 98%. This demonstrates the effectiveness of the toothbrush in promptly intervening in hard palate issues. To further enhance classification accuracy and results, we plan to integrate generative AI into our system. By combining multi-class classification with generative AI, we expect to increase productivity while significantly reducing global levels of severity and quality of oral health problems. Consequently, our modern toothbrush stands out as a key contributor towards improving international oral health outcomes through prompt restorations.

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