# Tooth Cavity Classification using Artificial Intelligence

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## Abstract

This research deals with accurate and efficient tooth cavity classification using deep learning techniques. A large dataset of images obtained by practicing dentists and those of the Kaggle dataset were used to train a convolutional neural network model. CNN architectures like Mobinet, Resnet and VGG16 were used to train and classify cavity as mild, moderate and severe. Different models were compared based on accuracy, loss, and number of epochs. The VGG16 model after training for 15 epochs, provided significant results with 90% accuracy on the test dataset used.

***Keywords**: Tooth Cavity Classification, Deep learning, Image Analysis*

## 1.0 Introduction

Early detection and intervention of oral diseases is crucial in dental healthcare in which Artificial Intelligence and deep learning along with image-based diagnostics is widely used [1-3]. This has led to development of automated systems for tooth cavity prediction and classification. Depending on the cavity, dental caries can be categorized as mild, moderate, and severe [4-6]. Advancements in convolutional neural networks makes it a popular choice for image analysis.

By identifying cavities at an early stage can prevent further decay and damage, allowing for more effective and conservative treatment options, which can ultimately help extend the overall lifespan of teeth [7-9]. Visual examination and radiographic methods are dependent on the expertise of the dentists and are time consuming. Hence, there is a need for automated systems to detect cavities which can assist accurate and efficient detection of tooth cavities. As a subset of machine learning models, deep learning models are built based on neural networks (NNs), which are biologically inspired programming architectures that allow computers to learn by observing patterns in data [10-14].

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After employing transfer learning from an ImageNet1k dataset, the ResNet-27 architecture demonstrated superior performance for cavity detection with an accuracy of 77.8% and sensitivity of 0.69. To enhance interpretability, the system generated visual explanations for its cavity diagnoses using LIME. As a result, the system was empowered to identify the presence of cavities and provide clear explanations of its diagnosis to the end user [15-18].

Computer-based diagnosis is increasing because of its capabilities in diagnosis and caries, which may not be seen by the naked eye, various techniques that are applied to dentistry, especially for the detection of cavities include adaptive neural network architecture, deep learning, an artificial multilayer perceptron neural networks, convolutional neural networks, backpropagation neural network, and k-means clustering [19-21]. While AI-based tooth cavity classifiers have exhibited encouraging results, certain limitations and obstacles need to be addressed. One of the challenges is the availability of annotated dental datasets, as the collection and labelling of large-scale datasets can be time-consuming and resource-intensive. Additionally, transferability of AI models across diverse populations and imaging techniques needs to be thoroughly evaluated. Deep learning algorithms have emerged as powerful tools for tooth cavity classification, enabling accurate and automated analysis of dental images. These algorithms, based on neural networks, can learn complex patterns and features directly from data, making them well-suited for dental diagnosis.

CNN is a deep learning algorithm specifically designed for processing visual data, such as images. It is trained on a dataset of dental images to learn patterns and characteristics linked to various categories of cavities [22]. While training, the CNN algorithm acquires the ability to optimize its internal parameters (weights and biases) by utilizing a labelled dataset. The algorithm consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers.

The objective of this research is to propose an AI-based tooth cavity classifier that can analyse dental images and accurately classify the state of tooth decay, as well as assess the level of severity of cavities, across all age groups. By training the classifier on a diverse dataset of dental images, it aims to harness the power of deep learning algorithms to enable automated cavity detection. The classifier has potential to eliminate human error and enhance efficiency of dental practice.

## 2.0 Design AI based tooth cavity classifier and system architecture

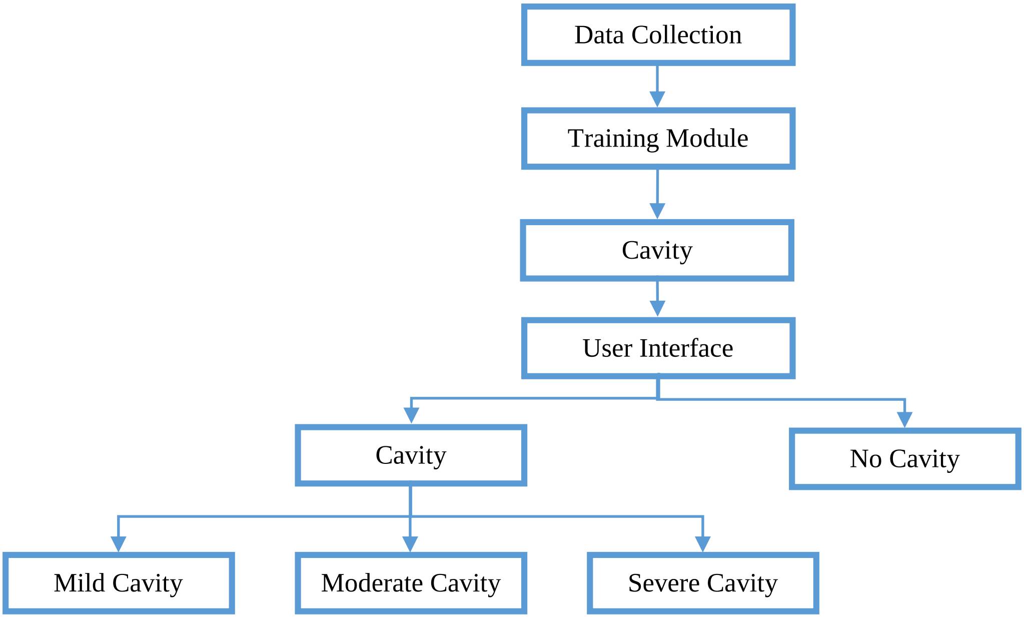


**Fig. 1**. Tooth cavity classification based on the data set

Fig. 1 shows classification of tooth cavity based on the data set obtained from practicing dentists, Kaggle dataset (images pre-processed by resizing). CNN architectures like Mobinet, Resnet and VGG16 were used to train and classify cavity as mild, moderate and severe. (source: Dr.Vani, Dr. Shashi Kiran, and the Kaggle dataset

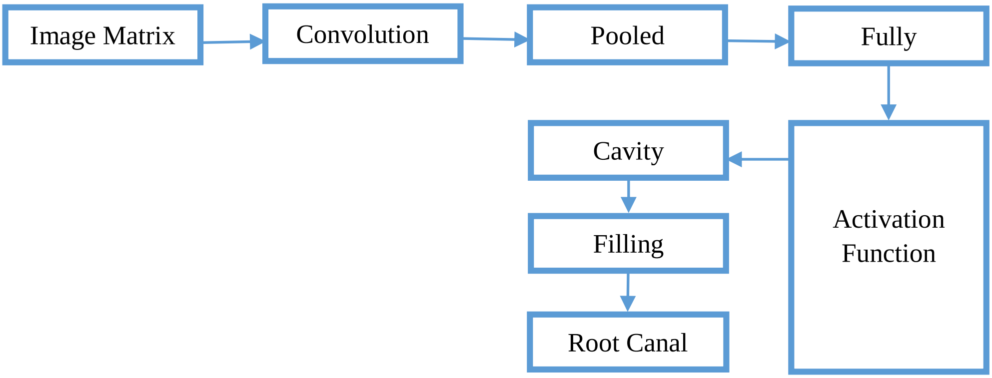


**Fig. 2** Architectural diagram for tooth classification

Fig. 2 incorporates an image matrix as input, which undergoes pooling to generate a pooled representation, followed by a dense layer that performs further processing for tooth cavity classification. It typically includes modules for image input, pre-processing, feature extraction using CNN models, classification algorithms, and an output module to display the classification results. Training dataset of 600 images and a testing dataset of 200 images were utilized**.**

**Table 1.** Distribution of caries and non-caries in a) trained and b) tested dataset

| Dataset | Carries (%) | No carries (%) |
|---|---|---|
| **Trained** | 54.9 | 55.1 |
| **Tested** | 45.1 | 44.9 |

Data pre-processing was performed in two steps namely, examining for null values and applying the forward fill method for filling them and dividing the dataset into training and testing sets as detailed in Table 1.

The model implementation involves the following steps:

- Collect and prepare a dataset of labeled dental X-ray images, including positive (with cavities) and negative (without cavities) as shown in Fig. 4.
- Choose and implement a suitable CNN architecture, including convolutional, pooling, and fully connected layers, for tooth cavity classification.
- Train the model using the prepared dataset, optimize the parameters using an appropriate loss function
- Evaluate the trained model performance using a separate testing dataset.
- Deploy the trained tooth cavity classifier ensuring adherence to ethical considerations and data privacy regulations.

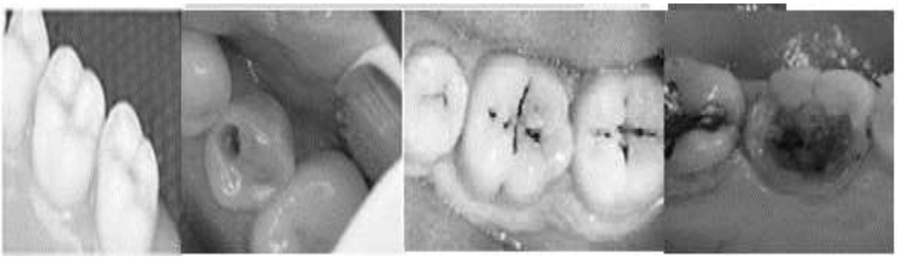

**Fig. 3**. Teeth cavity Detection

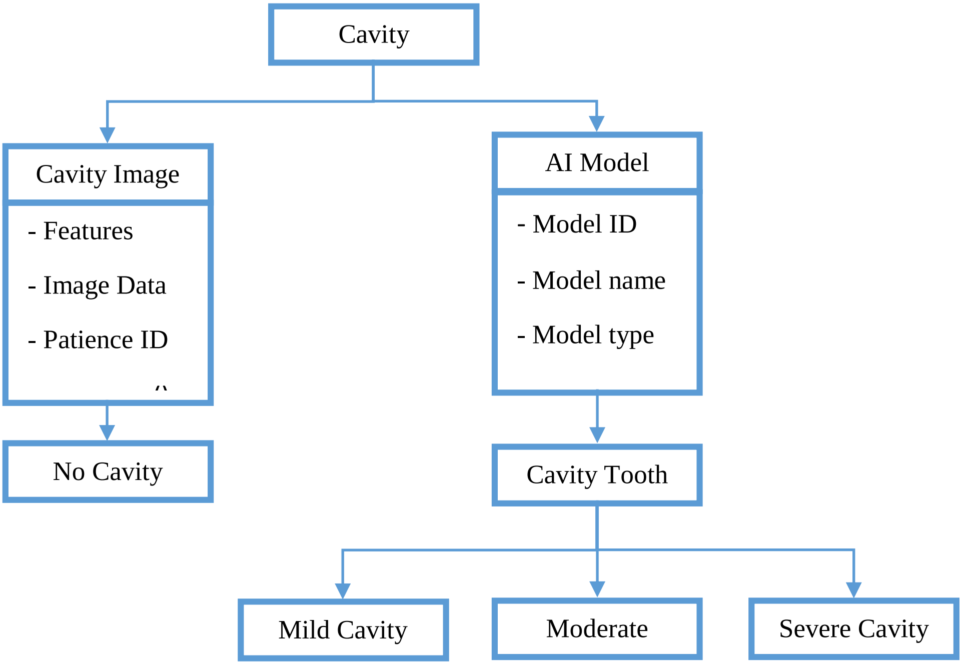


**Fig. 4** Cavity classifier for binary classification and training of AI models

Fig. 4 shows the cavity classifier for binary classification and training of AI models. Tooth cavity detection website provides an intuitive interface for users to access the cavity detection functionality, so users can click on 'Enter' to upload the images and detect the presence and absence of cavities and the severity of cavities and their classification. When users upload images (Fig. 5) of their teeth, they receive cavity predictions on the result page.


**Fig. 5**. Result of cavity detection

## 3.0 Modules of the webpage

**Data Collection** module enables collection of dental radiographic images for building the training and testing dataset. Dental image sources are used as input and gather dental radiographic images, ensuring data quality and diversity, and organizing them for further processing.

**Training Module** focuses on training the AI model, such as a CNN, using labeled dental images. It feeds the labeled and preprocessed data into the CNN model, optimizes model parameters through iterations, and trains the model to learn cavity classification.

**Cavity Classification module** aims to classify dental radiographic images and identify the presence of tooth cavities and applies trained deep learning models, like MobilenetV2, Resnet9, and VGG16, to divide the input images and predict tooth cavities.

### Working of CNN algorithm for tooth cavity classification:

Once the CNN architecture is defined, the model needs to be trained using the labeled dataset. During the process, CNN learns to optimize its internal parameters to minimize the prediction error. CNN consists of multiple layers including convolutional layers, pooling layers, and fully connected layers. The input layer of CNN accepts dental X-ray images. Each image is typically represented as a 2D matrix of pixel values in Fig. 6.

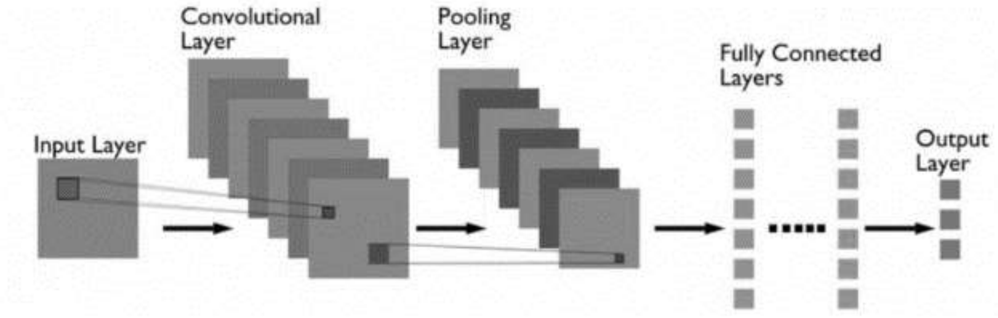


**Fig. 6**. Convolutional layers

Convolutional Layers are the core building blocks of CNN. They consist of multiple filters (also known as kernels) that convolve across input images to extract various features. Each filter performs element-wise multiplication and aggregation to produce feature maps. The number of filters determines the depth of output feature maps.

Pooling Layers down samples the feature maps by selecting the most prominent features and discarding the rest. Max pooling is the most common approach where the maximum value within a sliding window is retained, and mainly it reduces the dimension or size of input images.

Fully Connected Layers: The feature maps where the last pooling layers are flattened into a one-dimensional vector and passed through fully connected layers. Each neuron in the fully connected layers is connected to all neurons in the previous layer. These layers learn high-level representations and perform classification based on the learned features.

The output layer consists of neurons corresponding to the classes to be predicted. In the case of tooth cavity detection, it can be a problem of categorizing into classes like one with neuron for normal (no cavity) and another neuron for a cavity.

**Table 2.** Evaluation metrics of all models

| Model_name | No_of Epochs | Loss | Accuracy |
|---|---|---|---|
| VGG16 | 15 | 0.344 | 0.9074 |
| MobileNetV2 | 15 | 0.0463 | 0.8982 |
| ResNet9 | 10 | 0.8035 | 0.6197 |

Table 2 provides a comparison of different models based on their accuracy, loss, and number of epochs. It helps to evaluate the performance of each model in terms of accuracy and loss metrics and gives ideas to select the best model for further improvement.

Upon training the VGG16 model for 15 epochs, significant results were achieved with 90% accuracy on the test dataset.

## 4.0 Conclusion

An AI-based tooth cavity classifier was developed to predict and classify tooth cavities. The data collected from dentists and the Kaggle dataset were pre-processed by image resizing and dimensionality reduction. Multiple convolutional neural network (CNN) architectures, including Mobinet, ResNet, and VGG16, were utilized to train and classify the data. Integration of other dental image modalities, such as X-rays or 3D scans, can provide a comprehensive view of the cavities, leading to more robust classifications.

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