Dental cavity Classification of using Convolutional Neural Network

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Abstract. Dental and Oral diseases are very common diseases and half of the world population suffers from it. Due to poverty or unhygienic practices, these diseases are common, and it is estimated that 5% of total medical expenditure in the world is on oral diseases. In this paper, we have focused on detecting cavities. Recent developments in Machine Learning and Artificial Intelligence have helped a lot in medical science. Due to these algorithms, diagnosis and treatment of diseases can be done efficiently. To detect dental cavities different imaging modalities are used by doctors, however, in this paper we have used visual images of teeth’s and applied deep convolution neural network (CNN) to classify the teeth into caries or non-caries. We have used the images from the Kaggle dataset, and after tuning our model we were able to achieve 71.43% accuracy.

Keywords: CNN, Image processing, Deep learning

1. Introduction

As per WHO, it is estimated that more than 3.5B population encounter from oral problems. About 530 M youngsters endure from primary teeth dental cavities. Oral health care is costly and typically not part of universal health coverage (UHC). Dental care accounts for an average of 5 percent of overall health spending in most high-income countries and 20 percent of out-of-pocket health spending.[1][2]

Dental cavities, disorders like mouth cancers, oral forms of HIV, oro-dental injuries, cleft lip and palate, as well as noma, are the majority of oral health conditions. Almost dental problems are mostly avoidable as well as they can be treated earlier too. In most low- and middle-income countries, the prevalence of oral diseases continues to increase with increasing urbanisation and changes in living conditions. This is partly due to insufficient fluoride intake and inadequate access in the community to oral health care services. Rising intake of things that lead to earlier discussed problems as well as another non-communicable illness has contributed to the promotion of sweet foods and drinks, as well as tobacco and alcohol. As plaque forms on the surface of a tooth, dental caries generates and turn the free sugars found in foods and beverages into acids that over time kill the tooth. Continued high intake of free sugars, insufficient fluoride exposure, and a lack of toothbrushing plaque removal can lead to caries, discomfort, and infection and sometimes tooth loss.[3][4]

To detect the dental caries different imaging modalities are being used by the doctors. Figure 1[5] shows the different image modalities which can be used to detect dental caries. X-ray is one of the most used and available method[6]. Hidden dental structure, bone loss structure are some of the issues which
can be seen in X-ray and not by visual examination[7]. Whereas in radiography, continuous burst of X-rays is used to map and detect cavities, mass lumps and hidden dental structures.[8]

Figure 1. Imaging modalities in dentistry

Intra Oral: Essentially, to capture radiographic images that can be displayed on a computer or tablet, an intraoral imaging device is used. The acquisition of radiographic images is done by exposure to x-rays and is referred to as direct optical imaging. To simplify the method of collecting high-quality dental photographs for patients and relaying the visual information to them in a quick and effective way, an intraoral imaging system is used. The applied use of the parallel method is the ideal exposure procedure for intraoral camera systems. The parallel approach involves positioning a film around the axis of the patient's tooth (parallel to it).[9]

Extra Oral: The films are positioned outside the oral cavity in these radiographs, with the beam guided toward it. For cases that appear clinically with large lesions, this form of radiography may be used to study variants of the jaw, facial bones, to determine the growth of hard tissues, developmental abnormalities, fracture, and the temporomandibular joint.[5]

Computed tomography offers a good image of maxillofacial zone extensions of intracranial abnormalities such as lesions, haemorrhage, and trauma. It also helps to determine cyst and bone lesion
thresholds. The modified and refined CT technique of CBCT provides 3D imaging of maxillofacial structures. The radiation dose is low compared to CT which offers precise which intricate hard tissue data. Dentists may invest in their specifications, technologies and style of operation, thus reducing the total expense of the equipment.[10]

CNN is a part of deep learning algorithms which is especially used for analysing images. This algorithm is inspired by nature and is fully connected network, which makes it prone to overfitting. However, this algorithm requires little pre-processing which is a major advantage of CNN.[11]

2. Literature review

Researchers in their paper [12], used dataset of 3000 periapical radiographic pictures split into train and test dataset by 80-20 ratio. For pre-processing as well as TL (transfer learning) the pretrained GIVCN (GoogLeNet Inception v3 CNN network) utilized. For observation as well as distinctive execution of DCNN algorithm, the distinctive precision, reactivity, specificity, positive as well as negative predictive value, AUC as well as ROC had been calculated. Distribution of dataset of 3000 pictures was as maxillary (premolars-25.9% and molars-25.6%) and mandibular (premolars-24.1% and molars-24.4%). And according to diagnosis same dataset was distributes in dental carries (premolars-23.9% and molars-25.7%) and non-dental carries (premolars-26.1% and molars-24.3%). Then complete image dataset is not only resized to 299x299 image but also format is changed to JPEG format. The framework of Inception V3 had basically studied almost 1.28M images including 1000 object classes. The architecture involves 22 deep layers and also feasible to create various scale attributes by utilizing convolutional filters of any size within same layer. It utilized 9 inception modules with an auxiliary classifier, 2 fully connected layers as well as softmax functions. For training, 1000 epochs and 32 batches per epoch with learning rate 0.01 were executed. In order to enhance the detectivity by utilizing the best weights and boosting the output with the help of hyperparameters, fine-tuning was applied. Accuracy of diagnosis is 82.0% (75.5%-87.1%) of combining the accuracy of premolar as well as molar dataset. The DCNN got an AUC 0.845(95% CI 0.79-0.90) for the same.

The various image processing methods executed on that panoramic image dataset for predicting and classifying dental caries as well as different maxilla- facial pathologies. This paper [13] stated two different algorithms. One for prediction utilizing hybridized negative transformation and next for statistical texture analysis for the dental images containing cysts along with dental caries. GLCM was used to distinguish panoramic image texture. The generated attributes were contrast, entropy, correlation, homogeneity, and energy. They were utilized to detect boundaries for obtaining segmentation about the region of cysts. Results by both algorithms were acceptable relating to the maxillofacial radiologists’ diagnosis.

Dental caries can be predicted with the help of X-ray imaging too. This image includes teeth information relative to a particular diagnosis purpose. Dental caries can be detected in the Region of Interest. Noise, the intensity in homogeneities as well as low contrast, etc. makes trouble in detecting accurate ROI within a dataset. Segmentation of dataset K-means clustering to find ROI on pre-processed X-ray image dataset. Multiclass Support Vector Machine utilized for detecting dental caries automatically with help of texture attributes with high accuracy. [14]

Mostly cavity obtain due to consuming variety of foods and particles of that consumed food remains in a tooth. This creates bacteria and bacteria including the acid as well as saliva generate plaque. This becomes oral illness and makes black holes on teeth. The pre-processing of the dataset includes
histogram equalization, enhancement of contrast, and feature selection. The algorithm executed the Sobel edge identification using DCNN to detect the cavities with the efficient accuracy of 96.08%.[15]

3. Materials and Methods

3.1. Datasets

This study was conducted using the Kaggle dataset for teeth[16]. It contains visual representing images of cavity and non-cavity. The dataset comprises of 74 images in which 60 images were used for training purposes and 14 images were used for testing purpose. 45 images of caries and 15 images of non-caries were used for training purpose. Testing set contains 10 images of caries and 4 images of non-caries. Figure 2 shows the snapshot of the dataset.

![Figure 2. Snapshot of the dataset used](image)

3.2. Pre-processing and image augmentation

Images were in JPG format in the dataset. We have used ImageDataGenerator from keras.preprocessing.image in python. 20% of images from training were used for validation along with random horizontal flip. A zoom range of 0.2 was used randomly for zooming purpose for our model.

3.3. Architecture of the deep convolutional neural network algorithm

We have created a Sequential model which contains 10 layers. Architecture of the model is shown in Figure 3. Training dataset was used at a learning rate of 0.001 and 30 epochs were used.
Figure 3. Layers in CNN model

Layer 1- A Conv2D layer is used with ‘relu’ activation and input shape of (150,150,3)
Layer 2- Pooling layer is used of pool size (2,2)
Layer 3- Dropout layer is used of value 0.5
Layer 4- A Conv2D layer is used with ‘relu’ activation
Layer 5- Pooling layer is used of pool size (2,2)
Layer 6- Dropout layer is used of value 0.5
Layer 7- A flatten layer is used to flatten the image into 1-D array
Layer 8- A dense layer is used with 256 nodes and ‘relu’ as activation function
Layer 9- Dropout layer is used of value 0.5
Layer 10- A Dense layer is used with ‘sigmoid’ as activation function

Figure 4. Model summary of CNN architecture

| Layer | Output Shape | Parameters |
|-------|--------------|------------|
| conv2d (Conv2D) | (None, 150, 150, 32) | 2432 |
| max_pooling2d (MaxPooling2D) | (None, 75, 75, 32) | 0 |
| dropout (Dropout) | (None, 75, 75, 32) | 0 |
| conv2d_1 (Conv2D) | (None, 75, 75, 64) | 51264 |
| max_pooling2d_1 (MaxPooling2D) | (None, 37, 37, 64) | 0 |
| dropout_1 (Dropout) | (None, 37, 37, 64) | 0 |
| flatten (Flatten) | (None, 87616) | 0 |
| dense (Dense) | (None, 256) | 22429952 |
| dropout_2 (Dropout) | (None, 256) | 0 |
| dense_1 (Dense) | (None, 1) | 257 |

Total params: 22,483,985
Trainable params: 22,483,985
Non-trainable params: 6
Figure 5. Flowchart of steps involved in process.

Convolution Layer: The input is convoluted by convolutionary layers and transfers its result to the next layer. For its receptive region, each convolutionary neuron processes data only. Although it is possible to use completely linked feedforward neural networks to learn features as well as classify data, applying this architecture to images is not realistic. A convolution layer should have 3 things: width and height of convolution kernel, number of input and output channels, depth of input filters.[17]

Pooling Layer: To streamline the underlying computation, convolutionary networks can have local or global pooling layers. By integrating the outputs of neuron clusters on one layer into a single neuron on the next layer, the pooling layers minimise the data measurements.[18] Local pooling blends thin, usually 2 x 2 clusters. Global pooling works on all of the convolutional layer's neurons. In addition, a max or an average can be calculated by pooling.[19]

Any neuron in one layer is bound to every neuron in another layer by completely linked layers. It is the same as the conventional multi-layer perceptron neural network (MLP) in theory. By adding a particular function to the input values coming from the receptive field in the previous layer, each neuron in a neural network computes an output value. A vector of weights and a bias determine the function which is applied to the input values. Learning progresses by making iterative adjustments to these biases and weights in a neural network.

Dropout Layer: As discussed above, CNN is prone to overfitting due to its fully connected nature. To solve this issue, dropout is used which drops the nodes with a probability of 1-p at the training stage.
This is to validate the working of the model without some connections. After each iteration, the neurons are added back with their original weights.[20]

Flatten Layer: To input it to the next layer, flattening transforms the data into a 1-dimensional sequence. To create a single long function vector, we flatten the output of the convolutional layers. And it is related to the final model of classification, called a fully connected layer.[21]

4. Result and discussion

In the case of classification of dental caries and non-caries, our CNN model was created with binary cross entropy loss with learning rate of 0.001. However, the accuracy can be increased by increasing the dataset images. We tested the model by tuning hyperparameters and achieved a maximum accuracy of 71.43%.

![Figure 6. Training accuracy and loss with epochs](image)

5. Conclusion

With the progress of technology, medical science can take a boost in the diagnosis and treatment of diseases. With help of image enhancement techniques, many medical images can be corrected and can help doctors to diagnose or find the disease efficiently. With help of Machine learning and AI algorithms many complete automated processes are created which are helping doctors in specialized areas. This paper presents that, that a mobile application can also be created which users/patients can use to snapshot the dental caries and can get a result about the status of an issue, meanwhile with increase in dataset, the accuracy of the model will increase.

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