IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

DENTAL CARIES DETECTION AND CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT: Dental and oral problems affect 80-90% of the world's population. Oral diseases are frequent due to poverty and unsanitary behaviors, accounting for around 5% of global medical expenditure. Machine learning has made significant contributions to medical research. Dental professionals are tasked with identifying different types of dental problems, while the diagnostic procedure is underway. This paper introduces a convolutional neural network approach for caries detection and classification. we implement a dental caries detection system using a Convolutional Neural Network with the MobileNetV2 architecture for feature extraction. Train a CNN model to classify images into Three categories. These algorithms enable effective diagnosis and treatment of illnesses. We tuned our model and achieved 91% accuracy. Precision, F1-Score and Recall is 90.10%, 89.34%, 90.12%, respectively.

***Keywords*: Dental Caries, Detection, Convolutional Neural Network (CNN), MobileNetV2**

I.Introduction

A person's tooth is composed of dentin, pulp, and enamel. Bacteria found in the mouth can cause tooth infections. These medical conditions are typically classified as dental caries. Caries cause irreversible damage to the teeth and originate in the tooth cavity.[1] Dental cavities are prevalent worldwide, affecting around 60-70 percent of school-aged children and almost all adults. A type of chronic illness called dental caries is brought on by cariogenic bacteria. By breaking down sugar, this bacterium creates acid. It sticks to the teeth. It gradually demineralizes the tooth. The most common oral health issues include dental cavities, mouth malignancies, oral HIV, oro-dental traumas, cleft lip and palate, and noma. Almost dental disorders can be avoided and addressed at an earlier stage. thats why Early Detection is important.

Fig 1: Tooth (Healthy tooth and tooth decay)

Figure1 .shows the Dental caries .Dental caries are classified as normal, beginning, moderate, or extensive based on their severity. Early detection of dental caries can save money in the future by saving more invasive operations.[2]

Potential Hazards for Dental Cavities Tooth decay can result from extended stickiness of sugary liquids such as milk, ice cream, and honey. Frequently consuming these beverages encourages the growth of oral bacteria, which produces acids that erode teeth. This problem may worsen if acidic beverages are consumed all day. Since these drinks feed the bacteria that cause tooth decay, newborns who drink these beverages in their nocturnal bottles may also develop tooth decay. Tooth deterioration may result from plaque that is not eliminated quickly after eating and drinking it can lead to tooth decay.

Dentists generally nurse their patients with caries by taking out radiographs (x-rays).Using their bare eyes, they may examine the x-ray of their teeth jaw and identify cavities. This may lead to overlooking cavities that are already present or difficult to identify. Automation is necessary for several reasons. and the need for a second opinion to corroborate decisions.

we have studied and made a model for dental caries detection and how a convolution neural network is used to identify it.CNNs may increase the accuracy of detecting caries in their early stages, which is important for timely intervention and lowering the need for invasive therapies. In addition to improving dental health outcomes, this simplifies dental practice operations and empowers practitioners to make well-informed judgments and maximize available treatment options.

1.1Types of Caries:

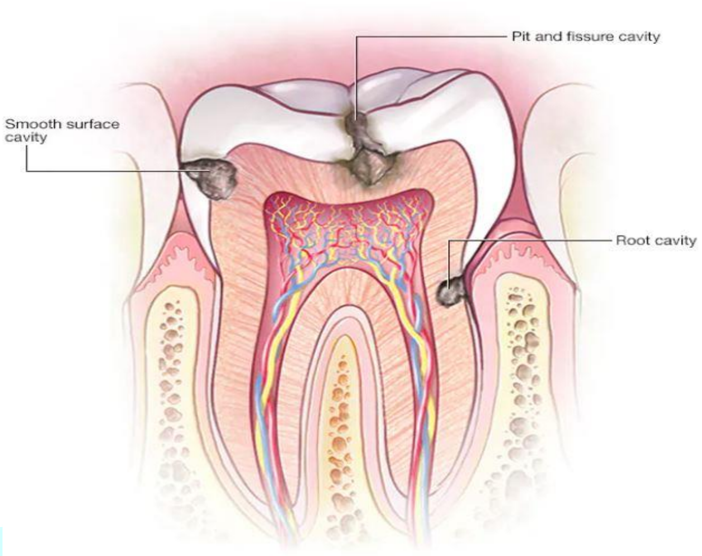

Fig 2: Types of Caries/Cavity

Pit & Fissure Caries develop in the grooves and fissures of teeth's chewing surfaces due to food and bacteria accumulation.They are important to diagnose because they can cause tooth decay and cavities, jeopardizing the tooth's structural integrity and perhaps causing discomfort and infection.

Smooth Surface Caries occur on the smooth surfaces of teeth owing to plaque deposition and bacterial activity.Detection is critical to preventing further advancement, since untreated smooth surface caries can evolve to bigger cavities, impairing tooth look and function.

Root Caries develop on the root surfaces of teeth due to gum recession and exposure to germs and acids.Detection is vital to avoid gum disease and tooth loss, because root caries can undermine the basis of teeth and lead to oral health concerns.

Table 1: Consequences of undetected caries

Caries type	**Consequence of Undetected Caries**	**Associated Dental Disease**
Pit and Fissure Caries	Risk of deep cavities, tooth decay, and potential need for fillings or root canals.	Dental caries (tooth decay)
Smooth Surface Caries	Increased risk of larger cavities, tooth sensitivity, and potential tooth loss.	Dental caries (tooth decay), gum disease (periodontitis)

Root Caries	Higher likelihood of gum disease, tooth weakening, infections, and possible tooth loss.	Gum disease (periodontitis), tooth decay (cavities), tooth loss (extraction)

The above table shows A Pit and Fissure Caries if undetected then there in Risk of Deep Caries and potential need for root canel. The Smooth Surfance Caries is Undetected then there is chnaces of gum disease like periodontitis. And if the Root caries is undetected then there is risk of tooth weakening infection and possible tooth and . and also a periodontitis disease. Thats why the detection of Caries is Important.

II.LITERATURE REVIEW

In the realm of dentistry, soft computing techniques including convolution neural networks, neural networks, and machine learning algorithms seem promise. As self-learning backpropagation algorithms, deep learning algorithms were created to help refine the output from the input data set while also boosting the efficiency of computers. Its CNN technique makes it popular in real-world scenarios as well as in the medical field. A neural network with one or more convolutional layers is known as a convolutional neural network. Neurones in these networks are capable of learning and possessing biases. In order to process an input function, neurons first use the dot product and then, if desired, a non-linear mapping function.

sonavane et al. have done research , they took visual images of teeth and applied a deep convolution neural network (CNN) to categorize them as caries or non-caries. They used photos from the Kaggle dataset, which includes visual representations of both cavities and non-cavities. The dataset consists of 74 photos, 60 of which were utilized for training and 14 for testing purposes. 45 photos of caries and 15 images of non-caries were used for teaching purposes. The testing set includes ten photos of caries and four photographs of non-caries. Their study proposes that a mobile application be developed that users/patients can use to picture dental cavities and obtain a result regarding the status of an issue; in the meantime, as the dataset grows, the model's accuracy will improve. After adjusting their model, They achieved 71.43%. [4]

Esmaeilyfard et al. there study reveals that deep learning models can correctly recognize dental caries and categorize their depths and kinds with excellent accuracy, sensitivity, and specificity.According to this study, dental cavities may be accurately identified and categorized using deep learning.There were 403 noncarious and 382 carious molar teeth in the CBCT imaging collection. Two sets of the dataset were created: a test set and a development set for training and validation. For every case, three images were gathered: coronal, sagittal, and axial. A multiple-input convolutional neural network (CNN) was fed the test dataset. For the provided samples, the network identified the lesions according to their kinds and depths and predicted whether or not there would be tooth decay. The detection and classification of dental caries were assessed based on F1 score, sensitivity, specificity, and accuracy.For caries identification in caries molar teeth, the diagnostic accuracy is 95.3%, sensitivity is 92.1%, specificity is 96.3%, and F1 score is 93.2%.The results for non-caries molar teeth were: F1score = 94.6%; accuracy = 94.8%; sensitivity = 94.3%; and specificity =

95.8%. When it came to identifying caries extensions and locations, the CNN network fared well in terms of sensitivity, specificity, and accuracy.[5]

III.MATERIAL AND METHODS

3.1 Convolutional neural networks (CNNs)

CNN are deep and feedforward networks. It is a multi-layered neural network that extracts sophisticated data choices from each layer to decide output. CNNs are suitable for activity tasks. CNN is commonly used for extracting information from unstructured data sets, such as photographs.CNNs are intended to handle data presented in numerous arrays as pictures, and their architecture consists of several steps. Dental caries are the most common dental illness in the world, and neural network technology and AI have become increasingly prevalent in dentistry. Many studies have contributed to detecting dental caries using neural networks and other dental pictures.[6]

3.2 MobileNet v2

The use of MobileNetV2 for pFeature Extraction has various benefits. First, its lightweight architecture enables efficient utilization of mobile and embedded systems with limited resources for processing. Second, MobileNetV2 achieves comparable accuracy to bigger, technically more costly models. Finally, the model's modest size allows for speedier inference times, making it ideal for applications that operate in real time.[8]

3.3 Design:

3.3.1 Dataset Collection

I have Collect that dataset from kaggle and Roboflow[12] The Dataset we have use has total 571 X-ray Images. From that we have used 378 images for training, 123 images for validation and 70 images for testing. The images are in jpg format. we have loaded these X-ray images to Google collab by resizing these images into the image size of 224 by 224.

3.3.2 pre-processing

Image resizing is crucial to ensure that all input images have the same dimensions.we have resized our image. then Normalization is performed to standardize the pixel values across all images. By scaling the pixel values to a range between 0 and 1, normalization ensures that the model's learning process is more stable and helps in avoiding issues such as vanishing or exploding gradients during training.

Segmentation is used as a preprocessing technique for obtaining features from dental X-ray pictures. Segmentation is performed using the Canny edge detection technique.The Canny edge detection technique is used to segment the input dental X-ray pictures to find edges, which aids in the extraction of significant information for future classification tasks. This segmentation phase improves the model's capacity to focus on key elements while removing noise and unnecessary information from pictures.The preprocessed image is then passed to the MobileNetV2 model for feature extraction

3.3.3 feature Extraction with MobileNetV2

Let I describe the input image, which is normally a three-dimensional array of pixel values. MobileNetV2 executes a number of convolutional and depthwise convolutional processes, followed by batch normalization and ReLU activation algorithms. This can be expressed as:

$$\text{Features} = \text{MobileNetV2}(I) \qquad (3.1)$$

This operation (Features) returns a feature that is a high-dimensional illustration of the input image, capturing distinct visual patterns and structures.

3.3.4 Custom Classification Layers

After feature extraction, the feature representation is passed through additional layers for classification.Let F represent the retrieved features from MobileNetV2. To minimize spatial dimensions, these characteristics are flattened or globally averaged, resulting in a one-dimensional feature vector.

Fflattened

Additional dense layers are applied to process these features:

$$\text{H1} = \text{ReLU}(W1 \cdot F\text{flattened} + \text{b1}) \qquad (3.2)$$

$$H1 = ReLU(W2 \cdot H1 + b2) \qquad (3.3)$$

Finally, a softmax layer is applied to obtain class probabilities:

$$Class\ Probabilities = Softmax(Wout \cdot H2 + bout) \ ()$$

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 mobilenetv2_1.00_224 (Func  (None, 7, 7, 1280)        2257984
 tional)

 global_average_pooling2d_1  (None, 1280)              0
 4 (GlobalAveragePooling2D)

 dense_42 (Dense)            (None, 256)               327936

 flatten_12 (Flatten)        (None, 256)               0

 dense_43 (Dense)            (None, 128)               32896

 dense_44 (Dense)            (None, 3)                 387

=================================================================
Total params: 2619203 (9.99 MB)
Trainable params: 361219 (1.38 MB)
Non-trainable params: 2257984 (8.61 MB)
```

Fig 3: Model Summary

The MobileNetV2 Functional Layer: This Layer represents the MobileNetV2 feature extraction model. It analyzes input photos and derives high-level information. The result shape suggests that it generates feature maps with dimensions of (7, 7, 1280). The number of parameters (Param #) provided below corresponds to the MobileNetV2 model's parameters, which include weights and bias.

GlobalAveragePooling2D Layer: This layer applies global average pooling to the output of the MobileNetV2 model. It compresses the spatial dimensions of the feature maps to a single vector of length 1280, yielding the output shape (1280,). Because this layer does not include any trainable parameters, the number of parameters is reported as zero.

Dense layers (dense_42, dense_43, and dense_44): These are fully linked (dense) layers that process and classify additional features. They use the output of the global average pooling layer as input. The output shape of dense_42 is (256,), suggesting that it has 256 neurons. The output shape of dense_43 is (128), showing 128 neurons. The final dense layer (dense_44) has an output shape of (3,), which represents the number of classes in the classification challenge. Each thick layer has a number of parameters, including weights and biases.

In short,The model is started with pre-trained weights from the ImageNet dataset, allowing it to extract high-level features from pictures.The feature extraction procedure in our project uses a pre-trained MobileNetV2 model to extract significant features from dental X-ray pictures. These traits are subsequently fed into a classification algorithm, which predicts the occurrence of dental caries.

3.3.5 Training the model

The model is trained with a categorical cross-entropy loss function and an optimization technique (such as Adam).During training, the parameters (weights and biases) of MobileNetV2, custom classification layers, and the softmax layer are changed repeatedly to minimize the loss between predicted probability and ground truth labels.

```
Epoch 1/10
15/15 [==============================] - 33s 2s/step - loss: 0.9764 - accuracy: 0.6176
Epoch 2/10
15/15 [==============================] - 29s 2s/step - loss: 0.7811 - accuracy: 0.6769
Epoch 3/10
15/15 [==============================] - 27s 2s/step - loss: 0.6547 - accuracy: 0.7143
Epoch 4/10
15/15 [==============================] - 26s 2s/step - loss: 0.5865 - accuracy: 0.7560
Epoch 5/10
15/15 [==============================] - 27s 2s/step - loss: 0.4929 - accuracy: 0.8044
Epoch 6/10
15/15 [==============================] - 27s 2s/step - loss: 0.3996 - accuracy: 0.8440
Epoch 7/10
15/15 [==============================] - 29s 2s/step - loss: 0.3333 - accuracy: 0.8725
Epoch 8/10
15/15 [==============================] - 27s 2s/step - loss: 0.2975 - accuracy: 0.9055
Epoch 9/10
15/15 [==============================] - 28s 2s/step - loss: 0.3061 - accuracy: 0.8703
Epoch 10/10
15/15 [==============================] - 28s 2s/step - loss: 0.2273 - accuracy: 0.9187
```

Fig 3:Model Training

Then We have Test the model and got 91% accuracy.Then we have created a button . an image upload button and a prediction button and classify button. To begin the categorization process, users just submit a dental X-ray image and click the prediction button. The model preprocesses and segments the picture, anticipating the existence of caries and classifying it accordingly. The findings, together with visuals, are shown in real time within the research environment, allowing users to assess the model's performance and learn more about its diagnostic capabilities. After click on predict button the result shown the image with Bounding Box Outside The caries. and then classify button after click on that The bounding Box image with predicted Class Name Displayed. (D0=Pit and Fissure Caries, D1=Smooth Surface Caries, D2=Root caries)

Table 2:System Parameters

Parameter Names	**value**
Hyper Parameters	Batch Size-32,Learning rate-0.001,Epochs-10
Operating System	Windows
Implementation	Keras and Tensorflow
Dataset	Training files=378,Validation files=123,Testing files=70
Image Size	224x224
Image Type	jpg

IV.Result and Discussion

In this part, we provide the findings from our proposed automated dental caries detection and categorization system. We evaluated the model's performance on a test dataset and reported several performance measures. our training Accuracy is 91% and Testing Accuracy is 90%

Table 3:Performance Metrics of Caries Detection Model

Metric	Value (%)
Precision	90.10
Recall	90.12
F1-score	89.34

Table 3 indicate that we have got Precision Recall and F1-Score is 90.10%, 90.12%, 89.34% Respectively.

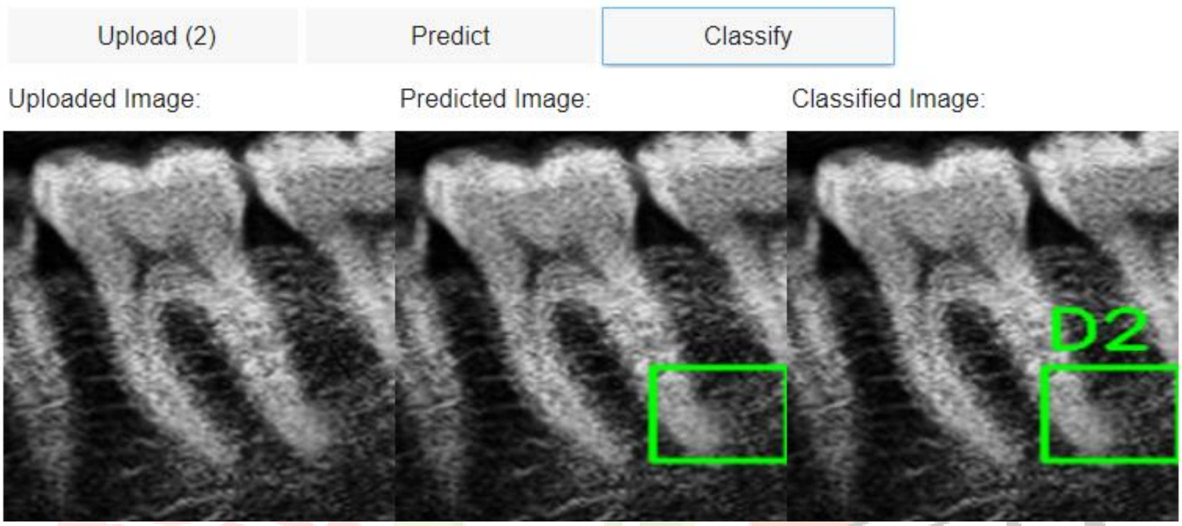

Fig 4: Result

Figure 4 shown the Result of our system . which shows Predicted Image of Caries . and the Classified image (D2) which is Root Caries.

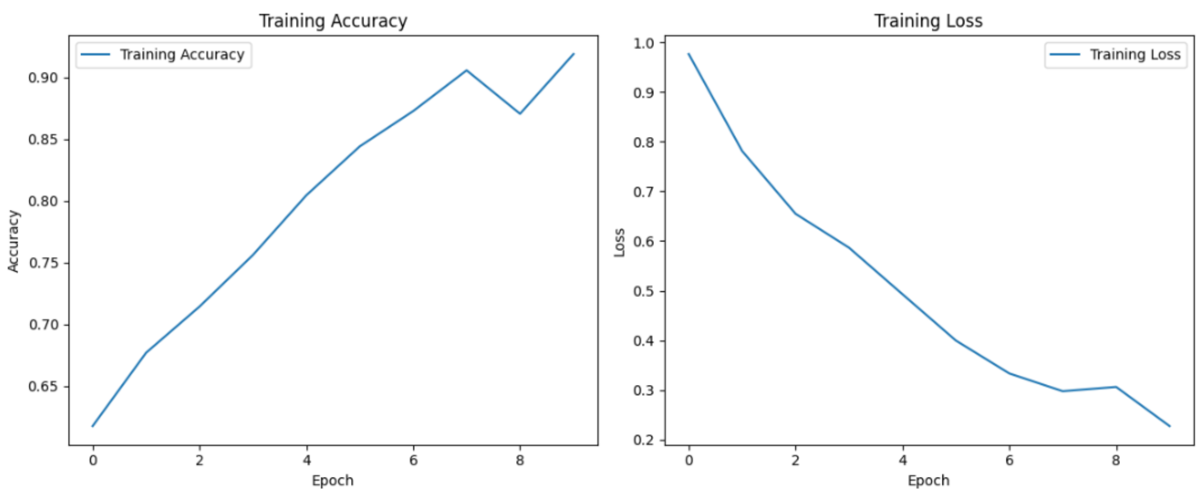

Fig 5: Traning Accuracy and Loss

As shown in Figure 5 the training accuracy steadily increases over epochs, while the training loss decreases

CONCLUSION

In this study, we suggested a novel technique for caries detection that combines canny segmentation and feature extraction utilizing the MobileNetV2 architecture. The major goal was to create an efficient and precise technique for diagnosing several forms of caries, including pit and fissure caries, smooth surface caries, and root caries, using dental X-rays. we have got 91% accuracy and 90.10%, 89.34%, 90.12% precision, F1 score and recall respectively.

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