A Novel Approach for Dental Caries Classification Using Transfer Learning

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Abstract*—Transfer learning has become a significant field of research in radiology. Periapical and panoramic radiographs have long been utilized by dental professionals to assist in the identification of the majority of dental problems. Dental practitioners usually treat tooth decay, also known as caries, physically based on the photographs they obtain from dental labs. To help with the enormous labor load on the healthcare society and for more precision, machine learning aids various smart vision systems based on computer applications. It also has better market demand. In order to provide novel techniques for fully automated tooth caries detection, this study has provided a framework for the recognition and evaluation of dental caries. The methods will make use of categorization and transfer learning techniques. First, using the provided OPG image as input, the suggested system will be able to identify the affected area of the tooth where caries are present. It will be possible to determine whether or not there is caries in the tooth after identifying the area that appears to be diseased. In addition to improving precision and accuracy, this method will also save up the radiologist's time. Dental cavities will be detectable by the X-ray machines, and the findings can be sent directly to the dentist for additional diagnostics.

Indexed Terms*—Dental caries, transfer learning, classification, Convolutional neural network, panoramic images, MI-DCNN (multi-input convolutional neural network), VGG16, ResNet50, MobileNet, Dataset, Comparison, OPG (oorthopantomography)

I. INTRODUCTION

Nowadays, tooth decay is a problem for people of all ages. To be treated, it must be found as soon as possible; otherwise, the patient may experience serious complications. The limitations or restrictions of prior diagnostic techniques will be eliminated by tooth decay detection, which will also assist the dentist in detecting caries at an earlier stage. Nowadays, dental illnesses or infections are chronic infections everywhere. Since adults use many harmful products in their daily lives, which is currently the main cause of concern as noted in the current assessment, the affection rate in all developed countries is 60–90% for school-aged children and close to 100% for adults.

Dental caries is the only outcome of a chemical reaction between fermentable carbohydrates and acid-producing bacteria in chemistry. Dental plaque contains an essential acid that starts the demineralization of enamel and dentin in microscopic fissures and along the smooth surface of teeth. The appearance of a white spot is the first indication of dental disease or caries. The small white spot becomes pitted and develops into very tiny holes in the dental surface known as cavities if the demineralization process is allowed to continue. It is most common in children between the ages of 5 and 10, as well as in teenagers and older children. However, everyone who has teeth, regardless of age, will undoubtedly have some evidence of caries or that white spot. The layers of that location increase day by day and can result in dental loss, pain, and other dental issues if those cavities or decay are left untreated.

The two names for dental images with particular definitions are periapical and panoramic radiography. The name "periapical" is made up of the words peri, which means "around," and apical, which means "end of the dental root." Periapical images usually capture the shapes, positions, and ideal sizes of teeth as well as the surrounding tissues. When taken from inside the mouth, it is referred to as an intraoral periapical picture and helps to capture the entire dental structure and its surrounding anatomy. Intraoral periapical radiography is widely used. We have complete understanding of the teeth and the surrounding bone thanks to this intraoral radiography.

The light film shows important data that can be used to diagnose dental diseases such gum disease, periodontal bone loss, dental abscesses, dental caries, or tooth decay. Additionally apparent are the alveolar bone, dental roots, and dental coatings that surround the affected teeth. This research may offer the chance to clarify crucial information about the condition of repairs, tooth fragments, and bone structure.

The dentist used panoramic and periapical images to manually identify cavities. The diagnosis may occasionally become less accurate due to the doctor's lack of training in that field or the number of patients being seen. Such circumstances may affect the diagnostic's accuracy, give tooth decay an advantage, and result in other health issues including infection or dental loss. The automated processes and machine learning-based systems for treating such disorders are advantageous for both people and dentists. In that area, productivity can be increased by image processing and computer vision, which can also help with data analysis and increase the efficiency of detection and classification. Data mining algorithms and intelligent approaches like classification algorithms and grouping patterns into comparable groups based on their properties can be used to analyze the data and identify pertinent patterns from the output. Some common dental conditions, including gingivitis, periodontitis, impacted teeth, and interdental bone disease, can be treated with the aid of the aforementioned technology. A few studies for diagnosing oral illness were also examined in the literature review.

In some subsequent papers, the methods like segmentation or detection have been studied; feature extraction is also there using deep learning methods; there are few studies where deep convolutional neural networks have been explored. Conventional machine learning algorithms and techniques have been used; if the dataset is so large then can further explore with deep learning, but for this study, transfer learning has been used.

The three pre-trained models—VGG16, ResNet50, and MobileNet—as well as the previously mentioned color picture dataset and panoramic photos have been employed in this proposed study to classify the images using transfer learning. There are 78 color images and 182 total images in the dataset of panoramic images. The dentist's ability to accurately classify the photos is the primary goal of developing such a model. Comparatively speaking, color photos offer the highest level of accuracy, which is thoroughly portrayed in the findings and analysis.

The following are the suggested model's main contributions:

A. The dataset has undergone data selection, data preprocessing, and augmentation to enhance the photos and rotate them approximately 6 degrees higher and lower without going beyond that. Brighten the photos more to highlight any locations where there are cavities.

B. A private dental clinic provided 182 panoramic pictures and 78 color images for the collection.

C. We investigate pre-trained models or architectures that are helpful for transfer learning. The model training cannot be restarted from scratch in order to reduce time waste.

D. The fundamental concept was to utilize many models on these two datasets and determine which one was superior. The created model has achieved remarkable accuracy on both datasets using the VGG16 pre-trained model.

The main goal of this suggested methodology is to create a model or system that may aid a dentist or other dental professional in classifying photos into two categories—caries and non-caries—using a deep convolutional layer.

II. LITERATURE REVIEW

The initial mention was made of oral disease detection, classification, and general investigations. Currently, there aren't many literature reviews available on the topic of identifying and categorizing photographs based on their attributes. For the extraction of statistical features, a back-propagation neural network was employed. Using the periapical pictures of 107 images, a detection accuracy of 91.67% for caries was made [1]. To increase the model's accuracy, researcher

Andac Simak created a multi-input deep convolutional neural network ensemble [2]. To create a new technology for fully automated dental decay diagnosis on permanent molars in youngsters between the ages of 11 and 19, Hongbing Yu explored unique tooth decay detection and evaluation platforms or frameworks. To separate a single tooth utilizing bitewing video, as described in Tsung-Yi Chen's suggested work for caries detection, they employed the CNN model to find cavities[4]. Deep learning models were used in a study on tooth decay detection by Lian Luya, but the accuracy it produced was poor due to a number of problems. The neural network and dentistry always improve the model's performance, and the classification in the outer dentin always has demonstrable accuracy and sensitivity for classification [5]. Deep learning may be applied to various dental pictures to diagnose tooth decay detection and classification with three types, including root caries, proximal, and occlusal, as proposed by Sarena Talpur in the literature [6]. Methods are employed in the study by Grace F. Olsen on image processing. They perform detection on data they receive as digitally colored photographs of tooth extract characteristics. However, the accuracy is only 85% [7]. A current review of ECC was provided by Marcus HT Fung. Discussed are ECC's clinical characteristics, management, causation, implications, and caries prevalence [8]. To help dentists determine which group of patients is most impacted, Stefano Clanettiet al. present a study on how to calculate the severity and prevalence of two separate dental diseases, decay disease, in several subclasses of social deprivation [9]. Lifa and Tian Hing In a study based on the ensemble method, Michel created a new model to do dental image classification as well as color image classification by combining the knowledge from all the models, such as VGG16, ResNet50, and MobileNet. their model's accuracy rate was 75%, which is typical[10]. Sergei Lawaro and Sergey brin conducted a study on a specific VGG16 convolutional neural network to classify images, and their model's accuracy was 80% because there was no augmentation in their model, and there was also less loss because the model was trained on the dataset from the first layer itself. However, it is not the same as transfer learning is the same as machine learning or dee[11]. In a study by Sergei Lawaro and Sergey brin on a specific VGG16 convolutional neural network to classify images, the accuracy of their model was 80% because the augmentation was absent in their model and the loss was also lower because the training on the dataset was given from the first layer itself if we train the model from the first layer itself then knowledge taken by that model is accurate but it is not like transfer learning is like machine learning or dee.

The dataset and the pre-trained model are compared in this suggested MI-DCNN model, along with their accuracy and data loss. The results of this study were sufficient to determine which model offers the maximum accuracy on which sort of dataset. Basically, the model using VGG16 offers the best color image accuracy, but somehow low panoramic image accuracy.

III. DATASET DESCRIPTION

Since the dataset is a crucial component of deep learning, the entire process is intended to train, test, and validate the data. As a result, the dataset needs to be correct and clean with a few common features in order to perform analyses on it. The dataset employed in this study consists of two different types: first, periapical color images; second, panoramic OPG (orthopantomography) images obtained from the Jaiswal dental laboratory. The color picture dataset includes 74 photos total—55 images with caries and 19 images free of caries.

There are 183 photos in the OPG (orthopantomography) dataset overall, of which 71 are caries-free and 112 are not. A dentist oversaw the photography of each shot. The sample photos from both datasets are displayed in Fig1.

A. Color Image dataset:

The term "color image dataset" refers to a collection of colored images. This dataset includes the caries and non-caries picture kinds, which are displayed below in Fig.1 and Fig.2.

Fig. 1: image with Caries

Fig. 2: Image with No-Caries

B. OPG (Orthopantomography) Dataset:

When a panoramic view, which combines both the top and lower jaws in a single photograph taken under the dentist's supervision. There are two different kinds of photos in this dataset. Images with and without cavities are shown in Fig. 3. Fig. 4.

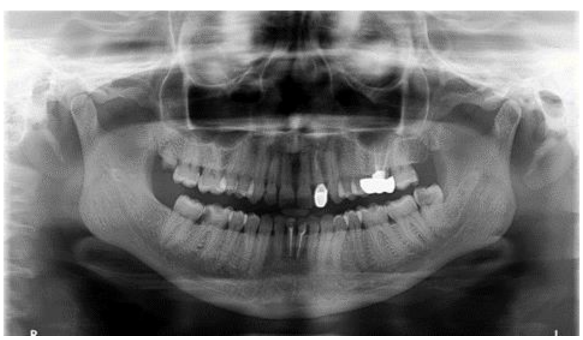

Fig. 3: Caries (Panoramic)

Fig. 4: Non-Caries(Panoramic)

Pie charts and graphs are two ways that data can be shown. The data summary will be more helpful if it is presented to other researchers. Data visualization is useful for identifying the percentage of data that is used for training and the percentage that is used for testing or validation. Figure 6 displays a depiction of the data in a graphic manner.

Figures 5 and 6 are pie charts with percentages. In the study, 75.0% of Caries photos and 25.0% of No-Caries images were used for training purposes. It used 28.6% of the non-caries photos and 71.4% of the caries images for testing. 30% for testing and 70% for training is the best split.

IV. PROPOSED METHODOLOGY

The feature extraction layers were the bottom layers that had been frozen to take the knowledge from the pertinent model, i.e., VGG16. This study demonstrates the use of the new model from the knowledge layers, which are feature extraction layers, and the training to the classifier or predictor layer, which is the top layer. Actually, this study compares the performance of the pre-trained model with that of the dataset. This study would be the first to analyze those dataset and pre-trained model parameters, using three pre-trained models: 1] VGG16 2] MobileNet 3] RestNet50. The suffix, for example, indicates how many layers are in the model. Deep, convolution, pooling, hidden, dense, dropout, flatten layer, and other layers are among the 16 layers that make up VGG16.

In essence, we created a new, empty model and copied the feature extraction layers from the previously trained model. Then, using the data from our dataset, we trained the model by fusing the classifier with MI-DCNN, or multi-input deep convolution neural network, layers. A thorough explanation of the suggested methodology is provided in the subtitle that follows.

4.1 STEPS OF PRE-PROCESSING

For particular photos, data augmentation is carried out during the pre-processing of the data. It is taken into account that data augmentation will flatten and rotate around the plain with a different angle, which will be harmful to model accuracy to avoid, and it is advised to use data augmentation with 6 degrees upper and lower the plain in this study's data on dental caries and non-caries. PreContrast improves the image's clarity, and shearing makes data appear good, therefore the data will undergo some pre-processing. For optimal results, data should be in tabular format with numbers in the text and be in comma-separated values (.csv) file format for transfer learning or deep learning. The Python albumentation library is useful for augmentation. the plain's upper and lower.

4.2 MODEL CONSTRUCTION

Transfer learning is the process of transferring an existing model's information to a fresh one. Basically, pre-trained models VGG16, Resnet50, and MobileNet were used in this work. The first time accuracy was measured, VGG16 was utilized, and it had the greatest accuracy of 75%.

The feature extraction layer has been frozen, the classifier or predictor layer has been removed from the model, the knowledge, or feature extraction layer, is connected with the new proposed model, training on color and OPG images has been completed, and the new model is now ready to be used for classification purposes. The included layers are: vgg16(functional), 14714688 parameters; flatten(Flatten), 0 parameters; dense(dense), 12845568 parameters; dropout, 0 parameters; dense-1, 131328 parameters; dropout_1, 0 parameters; dense_2, 514 parameters. Consequently, the proposed model's total number of parameters is 27,692,098. The model summary and convolution layers are displayed below.

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 7, 7, 512)	14714688
flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 512)	12845568
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 256)	131328
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 2)	514

Total Parameter	27,692,098
Trainable params	27,692,098
Non-trainable params	0

4.3 TRANSFER LEARNING

Transfer learning straddles the divide between deep learning and machine learning by taking the key information from the pre-trained model and intelligently transferring it to another model that is trained on a new dataset. This allows us to use the feature extraction layers from another pretrained model for user purposes even when we only have a small dataset.

For instance, if we know how to ride a bike, we can apply what we know about riding a bicycle because both have two wheels and somehow manage to maintain balance. We can only utilize the transfer learning model when the dataset we have is small and the user doesn't have enough time, according to the constraint.

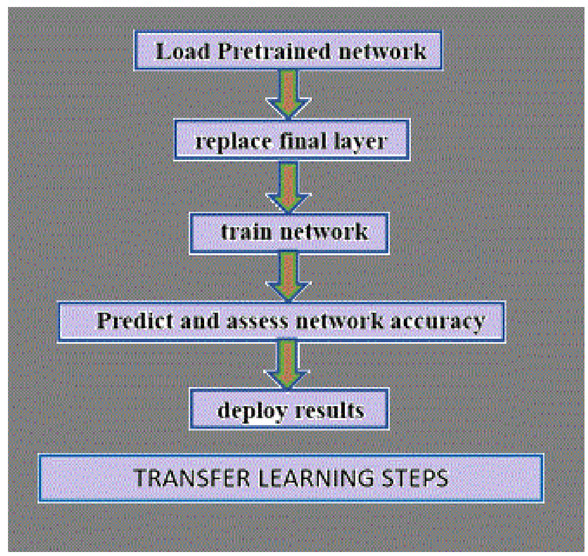

Fig.8 Transfer Learning

4.4 BENEFITS OF TRANSFER LEARNING

Quicken the deep learning procedure. Accuracy matters more than any deep learning model. Using a pre-trained model, developers can import the knowledge of one pertained network into another. Fine-tuning is an option if the dataset is substantial. Given how little actual data there is, applicable. Let's begin the training of the model from scratch. Easy to use. Saving time by avoiding the need for initial model training. Transfer learning will begin with the pre-trained model, but larger datasets also lead to more iteration, making the initial weights meaningless.

4.5 FINE-TUNING

Transfer learning fine-tuning is the process of training deep layers like vgg16, flatten, dense, dropout, dense_1, and dense_2 from scratch, but the difference is that we are not creating a deep learning model where we train the network from scratch here we are adding the knowledge of pretrained model to that we are giving the extra knowledge and information to the new convolutional neural network model for more accuracy we typically do it when we have the latencies.

This thus serves as a general introduction to transfer learning's fine-tuning. If fine-tuning was appropriate for this model, we had to train every layer from scratch, which would take a long time on the new dataset. Figure 9 below provides an explanation of the whole model.

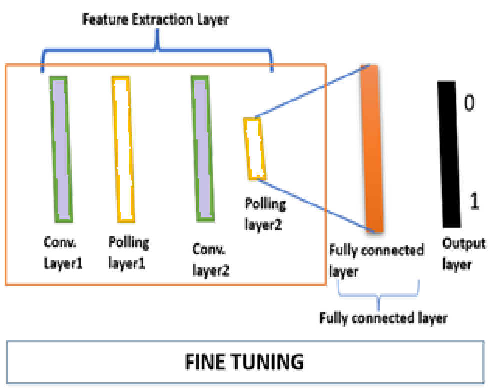

Fig.9 Fine Tuning

4.6 MULTI-INPUT DEEP CONVOLUTIONAL NEURAL NETWORK [MI-DCNN]

The neural network can be created for feature extraction and classification purposes. Depending on the requirements of the developers, it could have multiple layers. Accuracy is one of the parameters for which the deep neural network can be constructed since the neural network has to be trained on huge datasets in a way that will yield the best accuracy. In this study, we created a multi-input deep convolutional neural network, which combines a pre-trained model with a frozen feature extraction layer of the VGG16 and a final predictable layer that was trained on the newly acquired dataset. Now that the prior information has been merged with the knowledge that the most recent predictable layer has just been created, a new network has been created that we have named the multi-input deep convolutional neural network [MI-DCNN]. The new model is now ready to be put to use in order to produce results, determine accuracy, and draw a conclusion.

V. RESULTS

The LENOVO IDEA PAD with 1TB storage and 8 GB RAM was used for the testing work. The JUPYTER NOTEBOOK has been employed throughout for all coding needs. Both color and panoramic photographs of the dental periapical were obtained from one of the private dental labs in Nagpur. While creating this project, all ethical concerns were taken into account.

This study properly proposed the innovative multi-input deep CNN for dental image classification of dental caries. Multiple entries of the photos into the model have already taken the weight of the pre-trained model VGG16 into account. Later, the last trained layer on the new dataset and the froze feature extraction layer were appropriately integrated to create the new proposed model known as the Multi-input deep convolutional [MI-DCNN] layer.

This study has demonstrated the comparison of two parameters. The dataset comes first, followed by the trained models. Three different models have been employed in this investigation. (1) VGG16 (2) MobileNet(3) ResNet50. Color datasets and panoramic [OPG] photos are the two types of datasets used.

1] VGG16 and DATASETS

VGG16 does nicely with color images. After 50 epochs, the accuracy is roughly 75%, and on panoramic photos, it is all recorded at about 60%.

Table I: VGG16 vs. Dataset

MODEL NAME	DATASET	ACCURACY
VGG16	COLOR IMAGE	75%
	PANORAMIC	60%

2] MobileNet and DATASETS
When it comes to color photographs, MobileNet does well because it provides an accuracy of 73%, which is greater than panoramic images' accuracy of 59%.

Table II: MobileNet vs. Dataset

MODEL NAME	DATASET	ACCURACY
MobileNet	COLOR IMAGE	73%
	PANORAMIC	59%

3] ResNet50 and DATASETS
ResNet performs better on color photographs than Panoramic images, which have an accuracy of 60.94%, with a score of 71.67%.

MODEL NAME	DATASET	ACCURACY
ResNet	COLOR IMAGE	71.67%
	PANORAMIC	60.94%

So the comparison of all datasets and the three pre-trained models was the main focus of this.

According to the analysis, any pre-trained model's accuracy is significantly higher when applied to color photographs than when applied to panoramic images. The detection of a specific area is necessary, which is the future focus of this study right now. In some ways, this is because panoramic photographs encompass the entire area of the images, which has some kind of noise in the area that is not vital to give. According to the periapical dataset of color images, only a small fraction of the entire image is crucial for teaching and training the predictor layer. Additionally, there is the idea of layer freezing at the beginning of model development, which is significant for all pre-trained networks' analytical means.

CONCLUSION

As a result of technical improvement, dental imaging is always improving. These techniques and technologies will bolster dentists' professional expertise and help other professionals. It is possible to develop a system that aids in decision-making for dentists and other professionals by combining artificial intelligence with dental imaging. For this investigation, caries-prone teeth were identified using a dataset of color and panoramic photographs. The transfer learning technique was very helpful in categorizing the photographs and increasing accuracy by utilizing pre-trained model information. The proposed approach is based on the VGG-16 convolutional neural network model.

The last predictable layer of the model is trained with a total of 183 panoramic photos and 74 color images. A performance evaluation was conducted, and it was discovered that color photographs are more accurate than panoramic images. The analysis section explains why this is the case. The goal for the future is to improve accuracy for both the dataset and the dataset with caries identification and noise data removal from the image. The knowledge from all the models, specifically VGG16, ResNet, and MobileNet50, can be combined using the ensemble approach to improve the model's accuracy.

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