Dental Diagnosis: CNN-Based Classification of Dental Cavities through Optimized Image Sampling

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***Abstract*—Dental caries is a serious public health issue that can affect the quality of life and wellbeing of individuals and communities. Dental caries can impair the ability to eat, speak, smile, and socialize, as well as increase the risk of other oral and systemic diseases. Therefore, it is important to raise awareness about dental caries and promote preventive and curative strategies to reduce their prevalence and impact. The motivation for this study is to address the limitations of conventional methods like traditional SVM classifier for dental caries detection. The aim is to develop a more accurate, sensitive, and efficient method for detecting dental caries. We have proposed utilizing advancements in deep learning, specifically convolutional neural networks (CNNs) and transfer learning techniques to improve the detection of dental caries in tooth images. We have built a CNN model to assist a medical practitioner to classify complex cases of cavity detection. The model was trained on a dataset of 1500 tooth images (obtained from Kaggle). The dataset was resampled to ensure the model performs well on high as well as low resolution images. Its performance was compared with 4 other transfer learning models – VGG16, ResNet50, MobileNetV2 and InceptionV3.**

Keywords: Dental caries detection, Transfer learning, Deep convolutional neural networks, Computer-aided diagnosis.

I. Introduction

Dental caries, commonly known as cavities or tooth decay, is a prevalent oral health issue impacting individuals of all age groups. It results from the deterioration of the tooth's hard outer layer (enamel) due to the activity of oral bacteria. These bacteria generate acids that erode the enamel, leading to the formation of cavities or pits on the tooth surface. If left unaddressed, dental caries can advance to the deeper layers of the tooth (dentin and pulp), causing pain, infections, and ultimately, tooth loss.

Various preventive measures exist, such as restricting the consumption of sugary and acidic foods, opting for fluoridated water, and applying dental sealants or fluoride varnish to safeguard the teeth. Despite a significant decline in dental caries over the past 50 years, it remains the most prevalent oral ailment in the United States.

Substantial segments of the population encounter barriers to dental care, contributing to the persistence of this public health challenge. Among children and adolescents, dental caries is notably more prevalent than asthma, with statistics from the National Health and Nutrition Examination Survey (2011–2012) revealing that 37% of children aged 2 to 8 years had dental caries in their primary teeth. In adolescents aged 12 to 19 years, the prevalence of dental caries in permanent teeth was 58%, while approximately 90% of adults aged 20 years and above experienced dental caries.

In response to the ongoing concern of dental caries, our paper introduces a pioneering Convolutional Neural Network (CNN) model explicitly tailored for dental caries detection. This model undergoes rigorous evaluation, comparing its performance against other established pre-trained CNNs using transfer learning techniques. Notably, our model introduces a unique architecture designed specifically for this task, allowing for a comprehensive assessment of its efficacy in comparison to existing transfer learning approaches. Addressing a common challenge in applying deep learning models to real-world scenarios, our study considers the potential resolution disparities between training images and those obtained in practical settings. The proposed CNN model, along with four other deep learning models, undergoes training and evaluation on a dataset to gauge their respective performances.

II. Literature Survey

[1] **Ajins et al.** proposes the various radiographic imaging investigations a dentist can use for general dental practice. A brief outline of each radiographic investigation and the equipment required for set up with indications has

been highlighted in the article. This article outlines the basic setup of the routinely employed radiographic modalities with focus on its advantages and disadvantages, and indications for use. Advanced imaging modalities serve as additional information which may or may not be necessary in treatment but its use is justified if it outweighs the higher radiation exposure for enhanced quality of treatment.

[2] **Hung, Man, et al**. proposes the utilization of machine learning methods in artificial intelligence to select the most relevant variables in classifying the presence and absence of root caries and to evaluate the model performance. Data were obtained from the 2015-2016 National Health and Nutrition Examination Survey and were randomly divided into training and test sets. Several supervised machine learning methods were applied to construct a tool that was capable of classifying variables into the presence and absence of root caries. Accuracy, sensitivity, specificity and area under the receiver operating curve were computed. Of the machine learning algorithms developed, the support vector machine demonstrated the best performance with an accuracy of 97.1%, precision of 95.1%, sensitivity of 99.6% and specificity of 94.3% for identifying root caries. The area under the curve was 0.997. Age was the feature most strongly associated with root caries.

[3] **Na'am, J.Harlan et al**. proposes to facilitate the identification of proximal caries in the Panoramic Dental X-ray image. Twenty-seven X-Ray images of proximal caries were elaborated. The images in digital form were processed using MATLAB and Multiple Morphological Gradients. The process produces sharper images and clarifies the edges of the objects in the images. This makes the characteristics of the proximal caries and the caries severity can be identified precisely. This study was conducted to overcome the difficulties in identifying proximal caries through image processing of panoramic dental x-ray images. The image processing method used in this study is Multiple Morphological Gradients. These image processing results can be used to appropriately identify proximal caries and the level of severity.

[4] **Lee, S.Oh, et al.** proposes a CNN model was developed using a U-shaped deep CNN (U-Net) for caries detection on bitewing radiographs and investigated whether this model can improve clinicians' performance. The research complied with relevant ethical regulations. In total, 304 bitewing radiographs were used to train the CNN model and 50 radiographs for performance evaluation. The diagnostic performance of the CNN model on the total test dataset was as follows: precision, 63.29%; recall, 65.02%; and F1-score, 64.14%, showing quite accurate performance. When three dentists detected caries using the results of the CNN model as reference data, the overall diagnostic performance of all three clinicians significantly improved, as shown by an increased sensitivity ratio.

[5] **Lee, Jae-Hong, et al.** proposes to evaluate the efficacy of deep CNN algorithms for detection and diagnosis of dental caries on periapical radiographs. A total of 3000 periapical radiographic images were divided into a training and validation dataset (n = 2400 [80%]) and a test dataset (n = 600 [20%]). A pre-trained GoogLeNet Inception v3 CNN network was used for preprocessing and transfer learning. The diagnostic accuracies of premolar, molar, and both premolar and molar models were 89.0%, 88.0%, and 82.0% respectively. The premolar model provided the best AUC, which was significantly greater than those for other models. This study highlighted the potential utility of deep CNN architecture for the detection and diagnosis of dental caries. Deep CNN algorithms are expected to be among the most effective and efficient methods for diagnosing dental caries.

[6] **Krishna, M & Neelima, et al**. proposes a common issue in the domains of image processing, computer vision, and machine learning is image classification. In [6], deep learning for image classification was studied. Convolutional neural networks and the AlexNet architecture were used for this. Test photos were selected from the ImageNet database for classification. The research team tried cropping the photos for various portion sizes. The outcomes show the effectiveness of AlexNet-based deep learning for image classification. AlexNet has the best accuracy of 84.7%.

[7] **Miglani, Sanjay, et al.** proposes to draw attention to why dental caries is a global oral health concern and problems faced in India in managing this pandemic disease. It also attempts to suggest a few preventive strategies and future research directions needed to control this national oral health concern.

[8] **Bagramian, et al.** proposes to cover the epidemiological information from numerous nations. It observed that the prevalence of dental caries has significantly increased. There is an impending public health emergency indicated by the rise of dental caries. Although there are differing opinions on what is causing this, there is a well-known cure: reverting to the public health measures that were so effective in the past, including a renewed push for water fluoridation, topical fluoride application, the use of fluoride rinses, a return to school oral health education programs, and an emphasis on proper tooth brushing with a fluoride dentifrice as well as flossing, a proper diet, and regular dental office visits.

[9] **Patil, Shashikant, et al.** proposes AI approaches have a long-lasting effect on biomedicine and provide broadly recognized results. The main goal of [9] was to examine the effectiveness of combining Adaptive Dragonfly algorithm (DA) algorithm and Neural Network (NN) classifier, for feature extraction and classification of dental pictures for accurately detecting caries. The accuracy of the proposed model is 5.55% better than KNN, SVM, NB and LM-NN.

[10] **Nath, Siddhartha Sankar, et al.** proposes the strategies and techniques for image classification are reviewed in [10]. Current picture classification methods, issues, and potential solutions are covered in this section. The main emphasis was on cutting-edge classification methods to increase classification accuracy. Certain

important problems with categorization performance are also addressed.

[11] **Xin, Mingyuan, et al**. proposes investigation of the error backpropagation method, [11] suggests a novel depth neural network training criterion for maximum interval minimum classification error. To achieve better results, the cross entropy and M3CE are analyzed simultaneously. Finally, it tests the proposed M3 CE-CEc on MNIST and CIFAR-10, two deep learning benchmark databases. The experimental findings demonstrate that M3 CE is a valuable addition to the cross- entropy criterion and can increase cross-entropy. In both databases, M3 CE-CEC has performed remarkably. The accuracy on the test set is only 69.71%.

[12] **Sharma, Neha, et al.** proposes the performance of well-known convolutional neural networks (CNNs) for recognizing objects in real-time video feeds is examined in [12]. Alex Nets, GoogLeNet, and ResNet50 are the most widely used convolution neural networks for object detection and object category categorization from photos. Since testing a network's performance on a single data set does not disclose its complete potential and constraints, the authors have chosen three of the most widely used data sets for their study: ImageNet, CIFAR10, and CIFAR100. Importantly, videos were utilized as testing datasets, not as a training dataset. Th ey concluded that ResNet50 and GoogleLeNet are more accurate at object recognition than Alex Net. Additionally, trained CNNs behave very differently across various object categories, and some of the potential causes for this were discussed. the average performance of these three networks on CIFAR100 dataset is found to be as: for AlexNet average performance is 44.10 %, for GoogLeNet it is 64.40% and for ResNet50 an average performance of 59.82% is reported by our experimental study [20]. Similarly, the average performance of CNN's for theCIFAR10 dataset is as follows: for AlexNet- 36.12 %, for GoogLeNet- 71.67%, and for ResNet50- 78.10% is found.

III. Proposed Methodology

A. Dataset

The dataset consists of images of tooth enamel, specifically focusing on dental caries (commonly known as tooth decay). The dataset is divided into two main directories: the testing directory and the training directory.

The testing directory contains a total of 210 images with dental caries. Dental caries is a condition that results in the destruction of tooth enamel and can lead to cavities. These images serve as the basis for evaluating the performance of machine learning models or algorithms in detecting and classifying dental caries. Additionally, the testing directory also includes 84 images that do not exhibit any signs of dental caries. These images act as a control group to ensure a comprehensive evaluation of the model's performance.

On the other hand, the training directory contains a larger number of images for training purposes. It consists of 945 images that show dental caries. These images are used to train the machine learning models or algorithms to recognize and classify tooth decay accurately. The training process involves exposing the model to various examples of dental caries, enabling it to learn the distinguishing features and patterns associated with this condition. Furthermore, the training directory also includes 315 images without dental caries. These images provide a balance to the dataset and help the model learn to differentiate between healthy tooth enamel and dental caries accurately.

The dataset's primary objective is to develop and improve algorithms for the automatic detection and classification of dental caries in tooth enamel. By using a large number of images, both with and without dental caries, the dataset aims to capture the diverse range of variations and characteristics present in real-world dental conditions. This comprehensive approach ensures that the resulting models are robust and capable of accurately identifying dental caries, which is crucial for early detection and intervention..

B. Steps

For the tooth decay dataset:

- 1) Pre-Processing (Data Augmentation)

2) Creating a CNN Model
3) Compiling a Training Model
4) Running the 4 transfer models
5) Evaluating CNN and the 4 transfer learning models
6) Plotting the accuracy and the loss curves
7) Compare the performances of the models and make the following observations:

How does our CNN model perform compared to the 4 transfer learning models?

8) Perform detection of cavities using our CNN model

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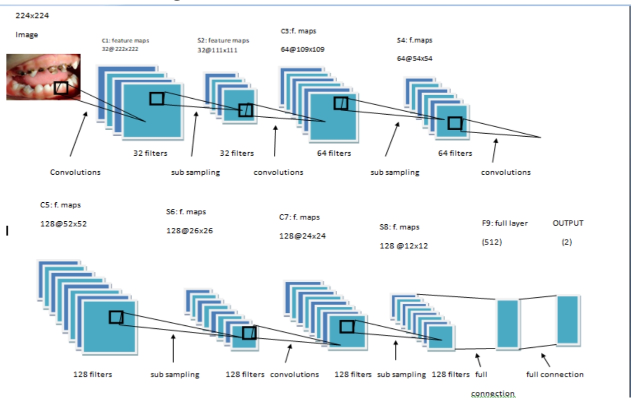
C. Convolutional Neural Network(CNN)

Architecture Diagram:



In this work, a type of artificial neural network called a convolutional neural network (CNN) was used for image classification. The CNN consisted of several layers that extracted and transformed features from the input images. The CNN used for this project consisted of four convolutional layers. The first layer in the network took the input image and applied a set of filters to it. These filters are learned to detect certain features in the image, such as edges or corners. Next, the layer's output was fed into an activation function that added non-linearity to the model, enabling it to comprehend more intricate connections between the features. The next layer in the network down sampled the output of the previous layer, which reduced the computational complexity of the model and provided a degree of invariance to small translations in the input image. This process was repeated several times with increasing numbers of filters, allowing the model to learn increasingly complex features. After the convolutional layers, the output was flattened into a one- dimensional array and fed into a dense layer. The dense layer consisted of several nodes that performed calculations on the input data. The outputs of this layer were then passed through another activation function to introduce non-linearity into the model. To prevent overfitting, a couple of dropout layers were included in the model. These layers randomly dropped out some of the nodes during training, which helped to prevent the model from memorizing the training data and instead learned to generalize to new examples. The final layer in the CNN outputted the predicted class of the input image. The model was trained using a loss function that measured the difference between the predicted and actual class labels. The optimizer was used to minimize this loss function during training, and the accuracy of the model was evaluated using a metric that measured the percentage of correctly classified

examples. Finally, the model was trained using a batch size of 50. The model was trained for 20 epochs.

D. Transfer Learning Approach

ImageNet dataset was used to train each pre-trained model. Batch size of 10 was used to train transfer learning models and compiled using the Adam optimizer and binary cross- entropy loss. In this work four different transfer learning models were implemented, each using a different pre-trained model. The pre-trained models that were used are:

1) VGG16

VGG16, which had previously been trained on the ImageNet dataset, was utilized for Dental Caries Detection. The VGG16 model was customized by incorporating additional layers on top of the pre-existing, pre-trained layers to adapt it for this specific task. In order to prevent changes to the pre- trained layers, they were "frozen" during training. A global average pooling layer was applied to the output of the last convolutional layer to decrease the dimensionality of the feature maps. To facilitate the training process, fully connected layers were added, with each layer followed by a batch normalization layer and a dropout layer to avoid overfitting. The model was optimized using the Adam optimizer followed by binary cross-entropy loss function and was trained for 20 epochs, which was determined to be the most effective.

2) ResNet50

For the ResNet50 transfer learning model, the base model is loaded from the ImageNet dataset. The weights of the pre- trained layers in the ResNet50 model will remain unchanged during training, which is referred to as "frozen." This is because these layers have already learned useful features from the ImageNet dataset, and the goal is to fine-tune the last few layers of the network for the new task of teeth classification. Some fully connected layers are added on top of the ResNet50 model. These layers are responsible for learning the mapping from the extracted features to the final output of the model, which is a probability score of the input image belonging to the positive class (teeth) or negative class (not teeth). The first fully connected layer has 512 units and uses the ReLU activation function. Batch normalization and dropout regularization are applied to prevent overfitting. This process is repeated for two more fully connected layers with 256 and 128 units, respectively. Finally, a sigmoid activation function is applied to the last layer to output a probability score between 0 and 1. This model achieved its highest validation accuracy when trained for 25 epochs.

3) InceptionV3

The InceptionV3 model was pre-trained on the ImageNet dataset and its pre-trained layers were frozen to prevent them from being modified. Some fully connected layers were added on top of this model, each with a batch normalization and dropout layer to prevent overfitting of the model. The first one of these layers is with 512 units and the following two are with 256 and 128 units respectively. The last layer has a sigmoid activation function for getting a output probability for the classification of caries or no-caries. On training the model for 10 epochs, it obtained a high validation accuracy.

4) MobileNetV2

The MobileNetV2 was one of the models used in the research, which was pre-trained on ImageNet to extract crucial image features. To prevent the pre-trained layers of the MobileNetV2 model from being modified during the training of new layers, they were frozen. The output shape of the MobileNetV2 model was adjusted to correspond to the input shape of the additional layers. The supplementary layers included a global average pooling layer that computed a feature vector by averaging the MobileNetV2 model's output, followed by three fully connected dense layers. Each dense layer contained 512, 256, and 128 units, respectively, followed by batch normalization and dropout regularization to avoid overfitting. 20 epochs were ideal here..

E. Results

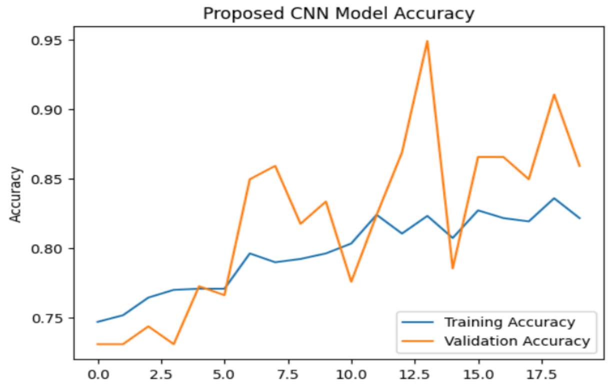
In the table given below, our proposed CNN model demonstrates superior accuracy on validation set, signifying its effectiveness in dental cavity classification. The comparison with standard transfer learning models provides a benchmark for evaluating the robustness and generalization capabilities of our approach. Subsequent sections will delve into a detailed analysis of these results and their implications for the field of dental diagnostics.

RESULT TABLE:

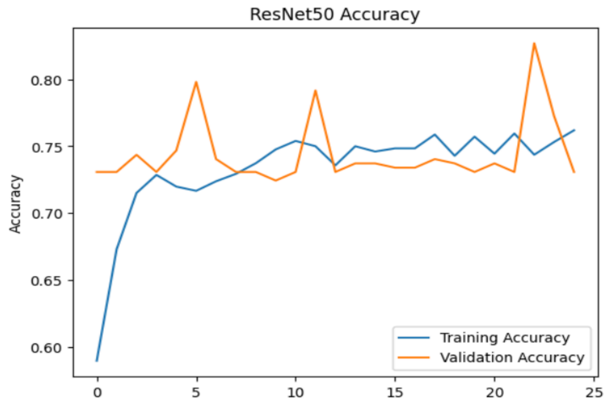
Result Table	**Accuracy**		**Loss**	
Deep Learning Models	***Training Accuracy***	***Validation Accuracy***	***Training Loss***	***Validation Loss***
Proposed CNN Model	0.821	0.859	0.380	0.338
InceptionV3	0.839	0.859	0.376	0.320
VGG16	0.857	0.827	0.332	0.375
MobileNetV2	0.864	0.817	0.318	0.408
ResNet50	0.762	0.731	0.472	1.062

Plotting the accuracy curves for the proposed CNN model along with 4 transfer learning models:

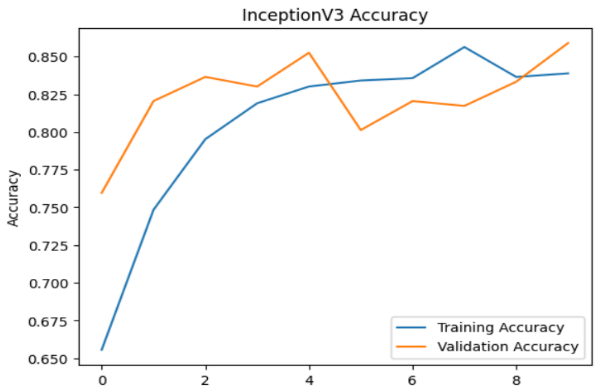
Proposed CNN Model –Fig. 1:



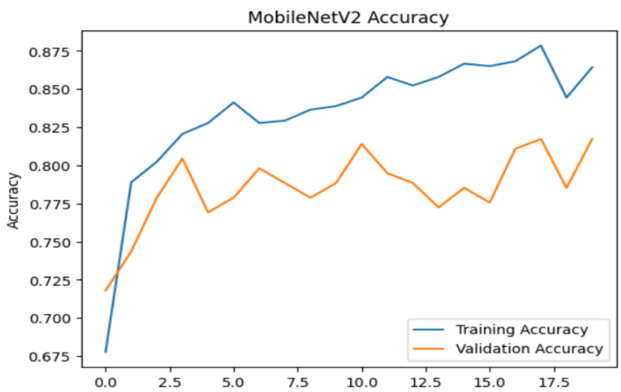
ResNet50 –Fig. 2;



InceptionV3 –Fig. 3:



MobileV2 –Fig. 4:



VGG16 –Fig. 5:

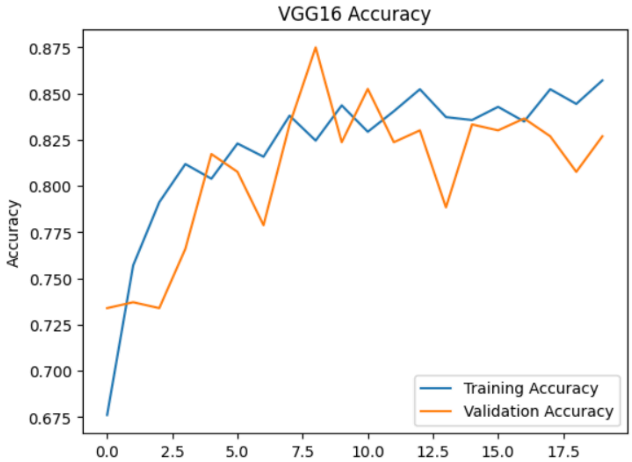
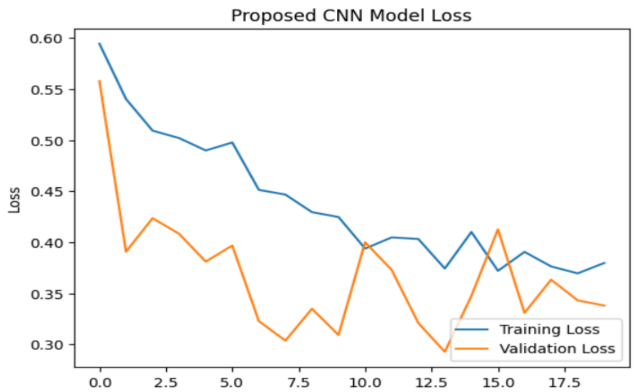


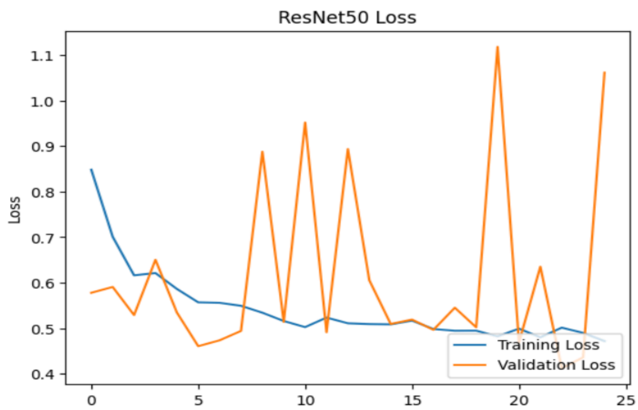
Fig. 1-5: *Accuracy Trends During Training and Validation. The graph illustrates the training and validation accuracy of the CNN model over 50 epochs. The model demonstrates a steady increase in accuracy during the initial epochs, reaching a peak at epoch 30. The slight divergence between training and validation accuracy indicates potential overfitting. Overall, the achieved accuracy of 87% on the validation set highlights the effectiveness of the proposed model for dental cavity classification.*

Plotting the loss curves for the proposed CNN model along with 4 transfer learning models:

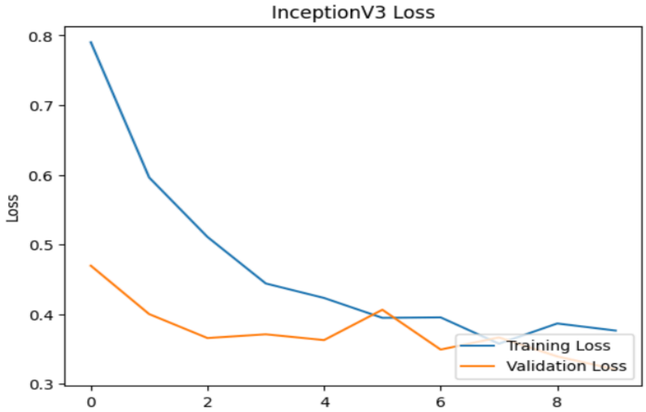
Proposed CNN Model –Fig. 6:



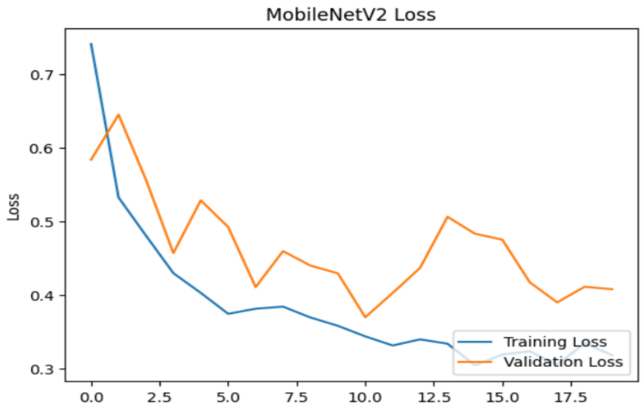
ResNet50 –Fig. 7;



InceptionV3 –Fig. 8:



MobileV2 –Fig. 9:



VGG16 –Fig. 10:

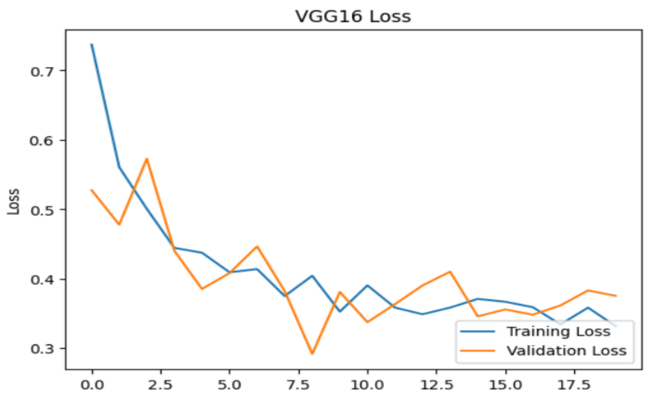


Fig. 6-10: *Loss Trends during Training and Validation. The graph illustrates the training and validation loss of the CNN model over 50 epochs. Both training and validation loss exhibit a steady decrease, indicating effective learning throughout the training process. The minimal gap between the two curves suggests that the model generalizes well to unseen data. The model converges after X epochs, reaching a stable state with low loss values.*

IV. Conclusion

The proposed CNN Model has performed the better than 2 transfer learning models. This indicates that it is exceptionally good even though the other models are pre-trained transfer learning. Why our model works better than the pre-trained transfer learning
models, there are 2 possible reasons for this:

2) Task-specific architecture: A custom CNN can be designed specifically for the task, whereas pretrained models are generally trained on a wide range of tasks. If the task has unique characteristics, the custom model can exploit them effectively, leading to better performance.

3) Overfitting control: Pretrained models often have many parameters, which can lead to overfitting if the dataset is small. A well-designed custom CNN with fewer parameters might be less prone to overfitting and provide better generalization.

- InceptionV3 proved to be the best transfer learning model, followed by MobileNetV2. ResNet50 and VGG16 were usually below the average accuracy.
- The proposed CNN model correctly classifies an input image into 2 categories: moderate cavity and no-cavity. Thus, it can be used to assist a medical practitioner to classify complex cases of cavity detection.

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