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CLASSIFICATION OF DENTAL CARIES DISEASE IN TOOTH IMAGES USING A COMPARISON OF EFFICIENTNET-B0, MOBILENETV2, RESNET-50, INCEPTIONV3 ARCHITECTURES

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Abstract

Dental caries is a global metabolic disorder, influenced by complex interactions between the body and microbes, it's caused by prolonged exposure to a low pH environment, leading to demineralized carious lesions. If untreated, it can cause pain and eating difficulties, requiring emergency care and significantly impacting overall quality of life. Diagnosis process can be conducted through physical assessment and analyzing laboratory testing. Image-based artificial intelligence systems, particularly the EfficientNet-B0 model, is suggested as a resolution for classifying dental caries using tooth images. The study's goal is to assess EfficientNet-B0's performance in comparison to other CNN architectures and play a role in advancing medical image classification technology. The original dataset comprising 1554 images was initially collected. After augmentation, the dataset expanded to 6348 images. The data was then divided into three subsets of training, validation, and testing datasets with a distribution ratio of 70:15:15, respectively. From all the evaluated models, the EfficientNet-B0 demonstrated a quite commendable accuracy of 0.98% with overfitting tolerance of less than 2%. Having the same accuracy as the MobileNetV2 (0.98%). Despite its inability to exceed the accuracy achieved by ResNet-50 (0.99%), EfficientNet-B0 accomplished its accuracy level with roughly a quarter of the parameters than ResNet-50 and highger than InceptionV3 (0.97%), highlighting its efficiency in parameter utilization and computational resource management. These findings hold promise for enhancing models and guiding clinical decision-making.

Keywords: *Caries, Convolutional Neural Network, Diagnosis, EfficientNet-B0, Image Classification..*

1. INTRODUCTION

Dental caries commonly known as tooth decay, is a widespread noncommunicable condition that affects approximately 2.3 billion people globally. It's a widespread chronic infectious disease affecting the oral cavity in humans, impacting a significant portion of the global population. [1], [2]. Dental caries is a complex disease influenced by various factors. It's primarily caused by the interaction of harmful bacteria in the mouth and other contributing factors, which leads to the gradual loss of minerals in specific areas of teeth [3], [4]. Factors contributing to the initiation and progression of dental caries encompass fermentable carbohydrates, oral colonization by cariogenic bacteria, a susceptible tooth (host), saliva quantity, and poor oral hygiene [3], [5].

The repercussions of dental caries are significant, as it can reach the inner layers of teeth, leading to toothaches, abscesses, infections, missed school days, speech and language development issues, tooth loss, and other long-term effects that negatively affect quality of life [6]-[8]. Additionally, it imposes financial burdens due to expensive treatments, cause oral malodor, and has broader implications for overall health, including its associations with systemic diseases such as cardiac problems, stroke, and respiratory disease. Globally, dental caries persists as a significant public health issue. In the realm of oral health, dental caries continues to affect diverse populations, irrespective of ethnicity, age, gender, or socioeconomic status. Despite extensive awareness efforts, dental caries remains a challenge, especially in low-income developing countries [1].

The utilization of Convolutional Neural Network (CNN) technology in image-based research, particularly in the realm of dental caries diagnosis, has demonstrated notable efficacy. Several investigations have leveraged architectures like VGG-19 and ResNet-50, achieving impressive accuracies of 94% and 93.30%, respectively [9], [10]. Nonetheless, ResNet-50 poses challenges due to its substantial demand for computational resources during both training and inference phases. Additionally, it can be susceptible to variations in the quality of the training data, potentially leading to issues such as overfitting or reduced generalization performance [11]. In light of these limitations, the EfficientNet architecture, particularly the B0 variant, emerges as a compelling alternative. EfficientNet B0 offers enhanced resource efficiency without compromising performance, thereby presenting a promising solution for tasks involving tooth image detection and subsequent classification [12], [13].

This study utilizing tooth images concentrates on caries classification through the implementation of the CNN architecture, specifically the EfficientNet-B0. By leveraging EfficientNet-B0, known for its computational efficiency and performance, the aim of this research is to overcome the constraints of alternative CNN architectures such as MobilenetV2, ResNet-50, and InceptionV3, particularly regarding computational resources and overfitting on smaller datasets. Additionally, the study seeks to conduct a comprehensive comparative analysis contrasting EfficientNet-B0's performance with that of previous CNN models. This comparative evaluation aims to enhance technology for classifying medical images and to enlighten the processes of clinical decision-making. Ultimately, the findings are expected to advance caries detection and classification methods, benefiting both patients and healthcare professionals.

The adoption of EfficientNet-B0 into a caries diagnosis system using tooth images is predicated on various correlated studies. Below are the particulars of these studies. highlighting advancements in using image analysis for caries detection. This study builds on these foundations, enhancing diagnostic accuracy and reliability in dental health by leveraging the model of EfficientNet-B0.

Research on Teeth disease was conducted by Jaiswal, et al. This research introduces a CNN model that employs different architectures like ResNet, AlexNet, and EfficientNet to classify deciduous and permanent teeth. The model underwent training on a dataset containing around 620 tooth images, including 314 images of mixed dentition and 306 images of permanent dentition. The panoramic radiographs used were taken from individuals aged 4-16 years. The findings exhibit outstanding recognition performance, particularly with EfficientNet-B0 and EfficientNet-B3. Both models attained remarkable accuracy, precision, and recall scores of 98% in discerning between deciduous and permanent teeth. This indicates that these models were highly proficient in recognizing patterns and features within the evaluated dataset [13]. Another research authored by Vinayahalingam et al. The MobileNet V2 was used in this study. The perfomance of this model showed 87% accuracy [14].

Mao et al. are conducting research pertaining to the classification of caries and restoration. In this study, several classifiers were used, such as Alexnet, GoogleNet, VGG19, and ResNet. The result showed that the use of Alexnet (90.30%) and GoogleNet (87.04%) resulted in the highest accuracy [15]. Recent research conducted by Lian et al. focuses on the detection and classification of caries. The data was divided into three categories. In the initial category, the Desnet 121 classifier attained an accuracy level of 95.7%, In the second category, an accuracy of 83.2% was achieved, while the third category, the attained accuracy was 86.3%. This demonstrates that the utilization of Desnet 121 can yield varied outcomes under different situations [16].

Deepak et al. By optimizing neural networks through deep transfer learning models, the study identifies the most effective model for classifying tooth images among SqueezeNet, ResNet-50, and EfficientNet-B0. Through evaluation and validation on three datasets comprising tooth images, a new deep learning model is assessed. Each model's output is then categorized based on the severity of edentulous areas, ranging from ideal/minimally compromised to substantially compromised, indicating the need for different levels of clinical treatment. Utilizing a dataset of 116 dental X-ray images, with 70% allocated for training and 30% for testing and validation, the findings reveal that the EfficientNet-B0 deep learning model achieves the highest accuracy rate of 98% [17].

From the previously discussed research, it is evident that several CNN architectures especially EfficientNet-B0 yield different results in classification tasks. Conducting a comparison study between the EfficientNet-B0 architecture and other architectures is crucial to determine the most suitable architecture for implementation in the tooth image dataset utilized by the author.

2. METODE PENELITIAN

2.1. Research Flow

This study employs a methodical and organized research approach to create and assess a model of Deep Learning designed for classifying caries images. The fundamental stages of this methodology encompass dataset, spilt data, data preprocessing, model training, validation, and model evaluation through measures such as precision, recall, and accuracy.

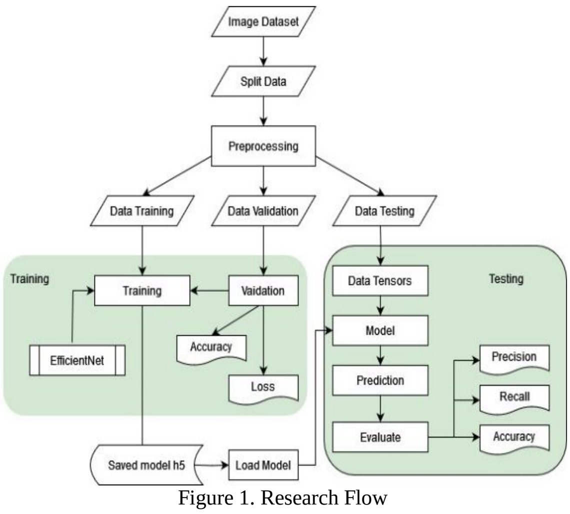

Figure 1. Research Flow

a. Image Dataset:

In the original dataset there are 1554 images from 2 classes, in each class there are (1155) caries images and (399) non-caries images combined in *.jpg format. The dataset provided by Sang Dinh from kaggle.

b. Split Data:

The dataset will be divided into three distinct parts to facilitate model training and evaluation. The larget portion, comprising 70% of the total data, will be allocated to the training dataset. This portion will be utilized for training the machine learning model, this section is designated for the training of the machine learning model, facilitating its acquisition of patterns and relationships inherent in the dataset. Additionally, 15% of the data will be designated as the validation dataset. Throughout the process of training, this set will be utilized to adjust the model's hyperparameters and determine its architecture, ensuring that the model generalizes well to new unseen data. The remaining 15% of the dataset will be reserved as the testing dataset. This final segment will be utilized after the model has been trained and validated to provide an unbiased evaluation of the model's performance. It helps to assess how well the model will perform in real-world scenarios with data it has never encountered before.

c. Pre-processing:

Pre-processing serves to streamline the handling of images sourced from existing datasets during the training phase. Initially, the dimensions of the images are set at 224 x 224 pixels in RGB format. The dataset originally contains 1554 images, divided into two classes: caries (1155 images) and no caries (399 images). The dataset within the scope of deep learning exhibits a relatively small size. To overcome this constraint, techniques for augmenting images are utilized to enlarge the dataset, thus enhancing the pool of images available for training purposes.

Following the augmentation process, the dataset underwent a substantial expansion, now comprising a total of 6348 images. To facilitate effective model training and evaluation, these images were meticulously distributed across three distinct subsets. Notably, (4586) of the images were allocated for training purposes, while (953) were reserved for testing, and an additional (809) for validation. This deliberate partitioning strategy ensures a robust evaluation of the model's performance, allowing for thorough testing on previously unseen data. By subjecting the model to such rigorous scrutiny, it's aim to develop classification models that are not only precise but also highly dependable. Therefore, it contributes to the advancement of the most advanced in image-based classification tasks. Various data preprocessing techniques were employed to enrich the dataset further, primarily through augmentation of the samples. This entailed applying various techniques, including rotation, shifting, and cropping, to introduce diversity into the samples.

After the preprocessing phase, the Deep Learning model proceeds to the training stage, utilizing the dataset augmented for improved performance. After the completion of the training procedure, the model is archived and subjected to assessment employing a distinct test set. Performance assessment involves the utilization of various metrics such as precision, recall, and accuracy. Subsequently, the acquired outcomes can then be juxtaposed with findings from other research studies, thereby facilitating the refinement of advanced models and their potential applications.

d. EfficientNet-B0:

The research team of Tan and Le began with EfficientNet-B0, emerged as a well-known example for its excellent performance in ImageNet transfer learning and image classification tasks. The EfficientNet collection contains numerous models, starting from B0 to B7, each designed to balance efficiency and effectiveness in neural network architecture [18]. Among these, EfficientNet-B0 stands as the foundational model, serving as the basis for subsequent variants. Its architecture, depicted in Figure 1, showcases a meticulously crafted design aimed at optimizing performance while maintaining computational efficiency. By leveraging a sophisticated scaling method, EfficientNet-B0 achieves remarkable accuracy levels across diverse image classification tasks, making it a pivotal component in contemporary deep learning research and applications.

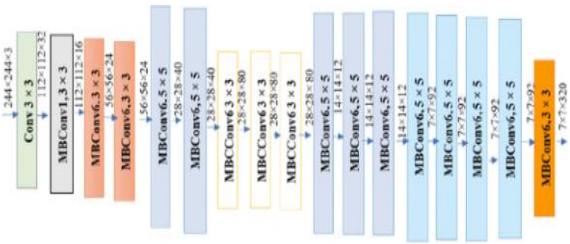

Figure 3. EfficientNet-B0 Architecture [19]

At the core of this structure lies the MBConv (Mobile Inverted Bottleneck), alternatively referred to as an inverted residual block supplemented with an additional SE block (Squeeze and Excitation). MBConv (Mobile Inverted Bottleneck Convolution) serves as the fundamental building block employed in the EfficientNet architecture, renowned for its computational efficiency in CNN models. The MBConv1 and MBConv6 architectures within EfficientNet-B0 are showcased in Figure 4.

The Mobile Inverted Bottleneck Convolution blocks inside EfficientNet-B0 presents variations specifically MBConv1 and MBConv6, every using distinct convolution kernels of the operations. Additionally, every MBConv block within EfficientNet-B0 integrates a Squeeze-and-Excitation block to enhance its efficacy. EfficientNet-B0 also uses a comprehensive measurement method known as efficiency measurement to optimize performance. This method aims to increase the image width, depth, and resolution of the CNN architecture to achieve better performance. [20].

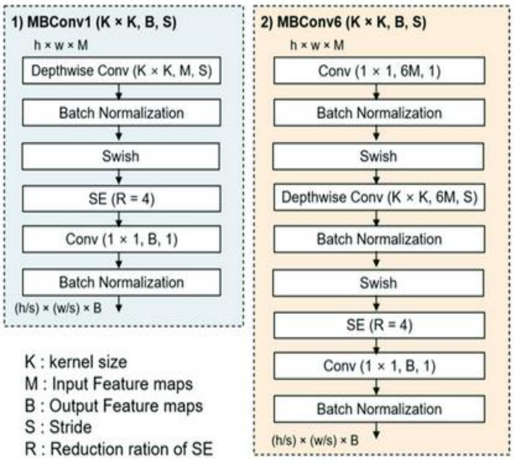

Figure 4. Mobile Inverted Bottleneck Convolution Blocks [20]

In the architecture of EfficientNet-B0, the MBConv is disabled for use at different levels or stages, where respective level/block represents a different depth and width relative to the total size of the architecture of CNN. These MBConv components are often used in conjunction with other components of the EfficientNet-B0 architecture, as illustrated in Figure 3. The architecture of EfficientNet-B0 is comprised of various elements, including MBConv1 and MBConv6 blocks, along with 3x3 convolution layers. Each component is distinguished by specific parameters, channels, and layers. Table 1 provides additional information on these parameters.

Table 1. Detailed Information of EfficientNet-B0

Operator	Resolution	Channels	Layers
Conv 3x3	224x224	3	1
MBConv1 3x3	112x112	32	1
MBConv6 3x3	112x112	16	2
MBConv1 5x5	56x56	24	2
MBConv6 3x3	28x28	40	3
MBConv6 5x5	28x28	80	3
MBConv6 5x5	14x14	112	4
MBConv6 3x3	7x7	320	1
Conv1x1 & Pooling & FC	224x224	1280	1

2.2. Parameter

Table 2 provides a comprehensive overview of the parameters employed for each architecture, offering insights into key elements such as kernel size and stride. These parameters play a crucial role in shaping the architecture's convolutional layers, determining the receptive field and spatial dimensionality of feature maps. The kernel size dictates the spatial extent of the convolution operation, influencing the level of detail captured from input images, while the stride determines the step size for sliding the kernel across the input volume. By understanding and fine-tuning these parameters, researchers can tailor the architecture to suit specific tasks and optimize model performance.

Table 2. Parameter of Each Architecture

No	Architecture	Kernel Size	Stride
1	EfficientNet-B0	3x3	2
2	MobileNetV2	3x3	1
3	ResNet-50	7x7	2
4	InceptionV3	3x3	2

2.3. Hyper-Parameter Value

Hyper-parameter values are the external configurations used to control the training process of machine learning models. Unlike model parameters, which are learned from the data, hyper-parameters are set before the training begins and remain constant. They can include settings like learning rate, batch size, number of epochs, and architecture-specific details such as the number of layers or units in a neural network. Proper tuning of hyper-parameters is crucial for optimizing model performance and avoiding issues like overfitting or underfitting, refer to Table 3 for details.

Table 3. Hyper-Parameter Values Of All Scenrios

Hyper-parameters	Value
Input Image	224x224
Batch size	16
Optimizer logarithm	Adam
Learning rate	0.001
Epoch	50

2.4. Architectures

The architecture of each method is illustrated in Figures 5, 6, and 7.

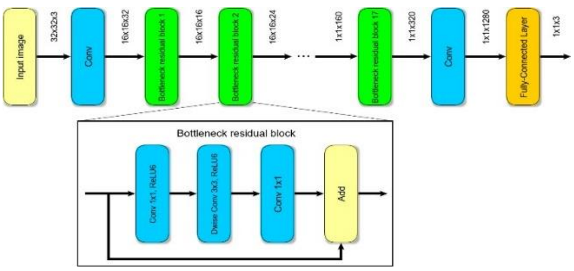

Figure 5. MobileNetV2 Architecture [21]

As illustrated in Figure 5 MobileNetV2, the successor comprises two blocks: a residual block with a stride of 1 and another with a stride of 2, utilized for size reduction tasks. Each of these blocks is composed of three layers: a 1 × 1 convolutional layer activated by ReLU6, depthwise convolution, and a subsequent 1 × 1 convolutional layer without non-linearity [21].

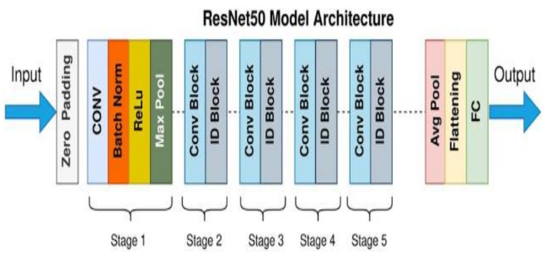

Figure 6. ResNet-50 Architecture [22]

ResNet-50 shows in figure 6, this architecture is a variant of ResNet, which achieved first place in the 2015 ImageNet Large Scale Visual Recognition Challenge (ILSVRC). Distinguished by its incorporation of residual connections, the ResNet-50 architecture allows for training deeper networks without encountering the issue of vanishing gradients. Comprising 50 convolutional and pooling layers, it stands out from other architectures in its usage. [22].

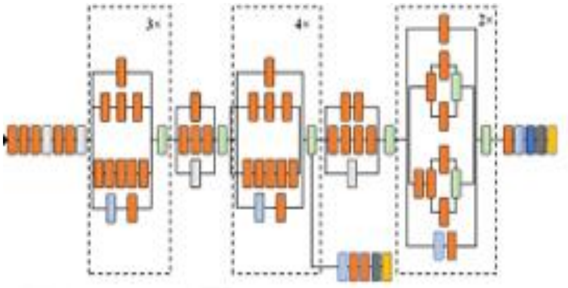

Figure 7. InceptionV3 Architecture [23]

Figure 7 is the InceptionV3 model consists of more than 20 million parameters and has been trained by a leading hardware expert in the industry. It incorporates both symmetrical and asymmetrical building blocks, with each block containing a variety of convolutional, average, and max pooling layers, as well as concatenations, dropouts, and fully connected layers. Furthermore, batch normalization is frequently employed on the input of the activation layer in this model. For classification, Softmax is utilized [23].

3. RESULT AND DISCUSSION

This study employed the architecture of EfficientNet-B0, using 224x224x3 input images to classify dental caries. During the training phase, a learning rate of 0.001 was set, and the Adam optimizer was used with a batch size of 16. The model was trained for 50 epochs, incorporating an early stopping mechanism to mitigate overfitting. Key evaluation metrics for gauging the model's efficacy encompassed accuracy, precision, and recall. Throughout the model development phase, RGB color space was utilized, and images sized 224x224 were employed for dental caries classification. Subsequent to rigorous training and testing protocols, the outcomes are delineated in Table 4.

Table 4. Evaluation of Each Architecture Regarding Accuracy, Precision, and Recall

Architecture	Accuracy	Precission	Recall
EfficientNet-B0	0.98	0.97	0.96
MobileNetV2	0.98	0.97	0.98
ResNet-50	0.99	0.98	0.98
InceptionV3	0.97	0.97	0.97

Table 4 presents the results of this study, showcasing the average accuracy achieved. Almost every model exhibits similar accuracies, with the EfficientNet-B0 model displaying an accuracy of 0.98%. However, the results of the EfficientNet-B0 model are not higher than the accuracies of the ResNet-50 models, which achieved an accuracy of 0.99%. The ResNet-50 model also obtained high precision and recall values compared to other models, with 0.98% for precision and recall, whereas the EfficientNet-B0 model achieved 0.97% for precision and 0.96% for recall, and the MobileNetV2 model obtained 0.97% for precision and 0.98% for recall.

The performance of the EfficientNet-B0 model demonstrates competitiveness, reaching an accuracy rate of (0.98%), slightly surpassing that of InceptionV3 (0.97%). Although it did not exceed the accuracies of ResNet-50, which stood at (0.99%), The achievement of the EfficientNet-B0 is noteworthy, as it attained a comparable level of accuracy with significantly fewer parameters, approximately one-fourth fewer. This underscores the EfficientNet-B0 architecture's ability to efficiently utilize parameters and manage computational resources. The findings highlight EfficientNet-B0's potential as a highly efficient and effective model for image classification tasks, suggesting a promising direction for enhancing deep learning architectures in terms of efficiency and computational cost. Moreover, these results underscore EfficientNet-B0's potential impact on improving clinical decision-making processes and driving advancements in medical image analysis.

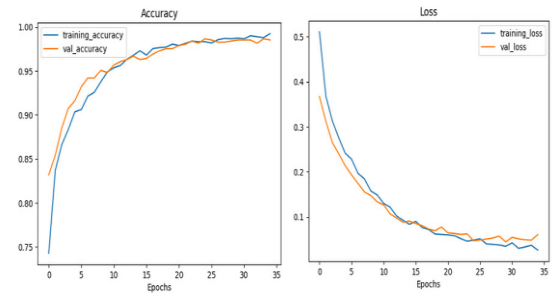

Figure 8. EfficientNet-B0 Accuracy and Loss Graph for The Dataset

Figure 8 shows how the EfficientNet-B0 model performs. This model achieved an accuracy of 0.98% after going through 50 learning stages. The learning process of this model took longer compared to others in reaching its best accuracy, which occurred at stage 35. Although EfficientNet-B0 has fewer parameters, it doesn't always mean it achieves its best accuracy faster. Larger models like ResNet-50 have a better effect in preventing overfitting and speeding up the learning process.

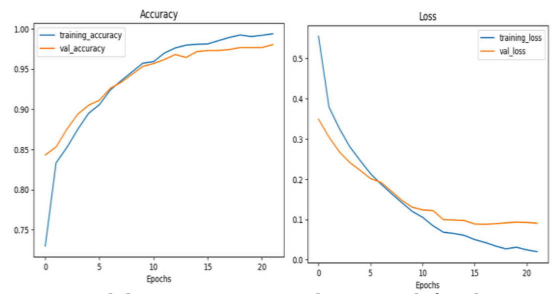

Figure 9. MobileNetV2 Accuracy and Loss Graph for The Dataset

Figure 9 is the results of the MobileNetV2 model, which ranked the same as EfficientNet-B0 with an accuracy of 0.98% at stage 22. This architecture is specifically designed for computational efficiency by using depthwise separable convolution layers to reduce parameter count and computational load.

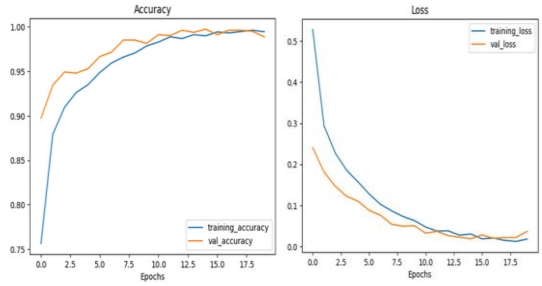

Figure 10. ResNet-50 Accuracy and Loss Graph for The Dataset

Figure 10 illustrates the outcomes of the ResNet-50 model, which attained the highest performance, achieving an accuracy of 0.99%, precision and recall of 0.98% at epoch 20. With a combination of diverse representations, strong regularization effects, the use of shortcut connections, and high training stability, ResNet has advantages that allow it to quickly reach the highest accuracy and converge at earlier stages.

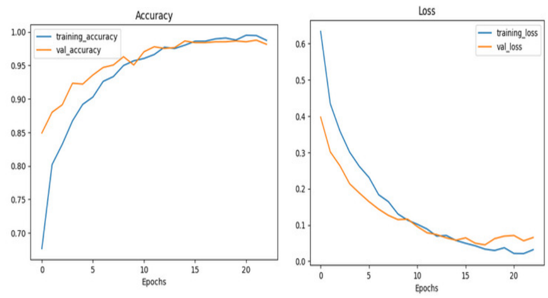

Figure 11. InceptionV3 Accuracy and Loss Graph for The Dataset

Figure 11 shows the results of the InceptionV3 model with an accuracy of 0.97%. InceptionV3 Using various types of filters within a single layer to effectively capture image features. Despite its complexity, this model is computationally efficient due to techniques such as factorized convolutions and batch normalization. InceptionV3 demonstrates high performance across various datasets, with excellent accuracy.

Figure 12 is the confusion matrix for the EfficientNet-B0 model reveals its performance in classifying image of "caries" and "no caries." The matrix shows that the model correctly identified 448 images as "caries" (true positives) and 485 images as "no caries" (true negatives). However, there were 14 images where the model incorrectly identified "caries" as "no caries" (false negatives), and 6 images where it misclassified "no caries" as "caries" (false positives). Overall, the model demonstrates a high level of accuracy, with a significantly greater number of correct classifications compared to misclassifications. This indicates that the EfficientNet-B0 model is effective at distinguishing between the two classes, making it a reliable tool for detecting the presence or absence of caries.

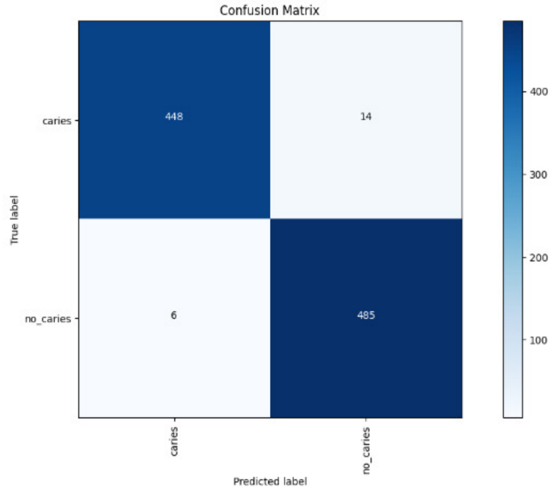

Figure 12. EfficientNet-B0 Confusion Matrix

Figure 13 shows the confusion matrix generated by the MobileNetV2 model provides a detailed evaluation of its performance in classifying dental caries. The matrix consists of four quadrants, each representing a different classification outcome. The top-left quadrant, containing 453 images, represents true positives where the model correctly identified the presence of caries. The bottom-right quadrant, with 479 images, indicates true negatives where the model accurately recognized the absence of caries. The top-right quadrant, which includes 9 images, represents false positives where the model incorrectly predicted the presence of caries in cases that were actually healthy. Conversely, the bottom-left quadrant, containing 12 images, denotes false negatives where the model failed to detect caries in cases that indeed had them. Overall, this confusion matrix illustrates the model's high accuracy in both detecting and ruling out dental caries, with minimal errors in classification.

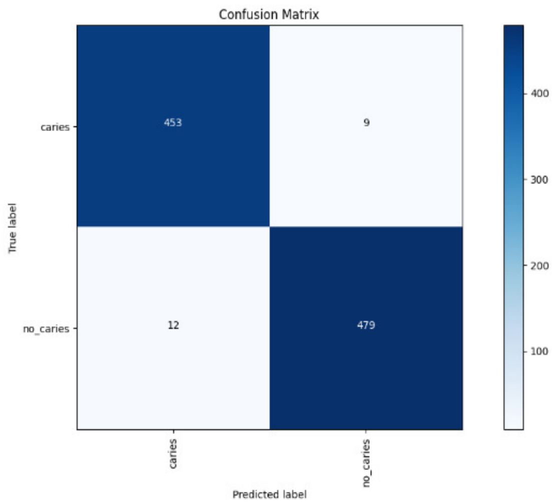

Figure 13. MobileNetV2 Confusion Matrix

The confusion matrix resulting from the figure 14 ResNet-50 model's, performance in classifying dental caries demonstrates its effectiveness with a high degree of accuracy. The matrix comprises four key sections: the top-left quadrant shows 458 true positive cases where the model correctly identified the presence of caries, and the bottom-right quadrant reveals 483 true negative cases where the model accurately detected the absence of caries. The top-right quadrant, containing only 4 images, represents false positives where the model incorrectly predicted caries in healthy images. Conversely, the bottom-left quadrant includes 8 false negatives, indicating images where the model failed to detect existing caries. This distribution signifies the model's robust capability in both identifying caries and confirming their absence, with a minimal margin of error. Compared to the previous EfficientNet-B0 and MobileNetV2 model, the ResNet-50 exhibits a slightly better performance in terms of reducing both false positives and false negatives, indicating its superior precision and reliability in dental caries classification tasks.

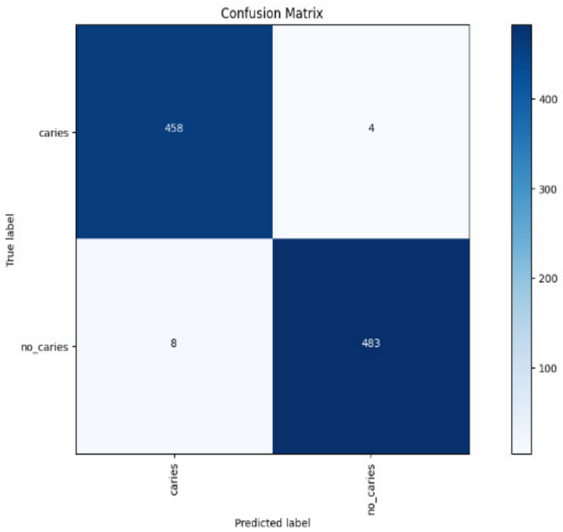

Figure 14. ResNet-50 Confusion Matrix

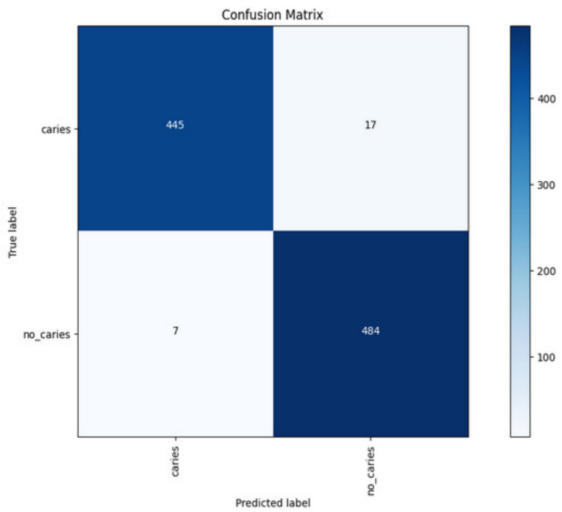

Figure 15. InceptionV3 Confusion Matrix

Figure 15 shows a confusion matrix for the InceptionV3 model's performance in classifying dental images for caries. It shows that the model correctly identified 465 cases of caries and 484 cases of no caries. However, it misclassified 17 cases of caries as no caries and 7 cases of no caries as caries. This matrix highlights the model's high accuracy and reliability in distinguishing between the two classes, with few misclassifications.

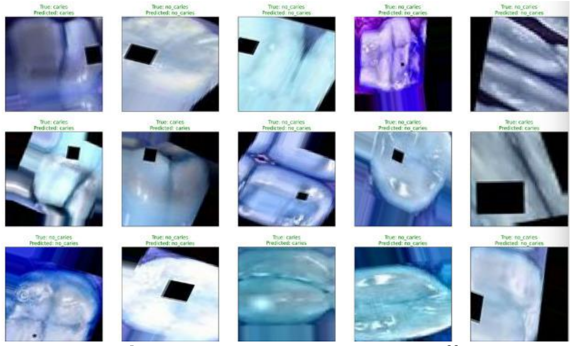

Figure 16. Prediction From Test Image Set Using EfficientNet-B0

In the evaluation of the EfficientNet-B0 model's performance on the test dataset, a comparison is made between the true labels of each image and the labels predicted by the model. This evaluation yields several metrics that provide a comprehensive overview of how well the model performs classification. Accuracy is the primary metric, measuring how often the model correctly predicts labels that match the true labels of all the images in the test dataset. Precision measures how accurately the model predicts positive classes out of all images predicted as positive, while recall measures how well the model finds all truly positive images out of all truly positive images. In cases where all 15 sample images have the correct predictions, it indicates that the EfficientNet-B0 model has identified each image correctly according to the given labels. This demonstrates excellent performance of the model in classifying those images. However, the evaluation of model performance should also consider variations in the test dataset and the possibility of biases that may affect prediction outcomes.

4. DISCUSSION

In this study, several models were developed to classify dental caries in tooth images into two classes: caries and no_caries. The four trained models achieved high accuracy levels, with only minor differences between them.

Two academic papers have presented the performance results of EfficientNet-B0. Oztekin et al. Proposing machine learning models for automated dental caries identification could result in earlier treatment interventions. With a dataset consisting of 1160 panoramic radiograph images showing caries and 1040 images without caries, the aim was to predict dental caries. Three well known pre-trained models EfficientNet-B0, DenseNet-121, and ResNet-50 were evaluated to identify the most efficient one in caries detection. While all three models yielded comparable results, ResNet-50 demonstrated slightly superior performance compared to EfficientNet-B0 and DenseNet-121. It achieved an accuracy of 92.00%, sensitivity of 87.33%, and F1-score of 91.61%, ResNet-50 surpassed the other models. Visual inspection confirmed that heat maps corresponded well with regions indicating caries. Therefore, the suggested interpretable deep learning model consistently and accurately diagnosed of dental caries [24].

Salunke et al. examined and tested the usage of CNN compared to several other deep transfer learning models, including VGG16, ResNet-50, Inception3, EfficientNet-B0, EfficientNet-B7, and AlexNet. Out of a total of 1336 images extracted from radiovisiography (RVG), 1104 images underwent training allocation, 111 for validation, and 121 for testing. With a learning rate of 0.0001 and spanning 100 epochs, the CNN model, featuring six convolution layers, achieved remarkable results with precission reached 94.59%, recall 95.89%, specifity 91.66%, and f1-score 94%, with a testing accuracy averaging at 94.2%. It turns out that the performance of this CNN is better than other models, including EfficientNet-B0. Although EfficientNet-B0 has a broader and deeper network architecture, resulting in the utilization of more parameters on the dataset, it only achieved an accuracy of 80.85% [25].

Compared to other studies, this research demonstrates equally high accuracy for each model. This particularly indicates that the EfficientNet-B0 model is highly effective and can be successfully applied in various other studies that use different datasets with relatively small sample sizes.

5. CONCLUSION

Based on the completed research, the author can draw several conclusions. The kernel size of 3x3, 256 neurons, and a dropout rate of 50% was implemented to mitigate overfitting. The learning rate was set at 0.001. Utilizing an image dimension of 224x224 pixels, the ReLU activation function was employed for normalization. Overall, this research underscores the outstanding performance exhibited by the EfficientNet-B0 model in tooth image classification when contrasted with alternative architectures. The model demonstrates remarkable accuracy and efficacy in extracting image features, thereby enhancing classification outcomes. Consequently, EfficientNet-B0 stands out as a promising architecture for tooth image classification, warranting strong consideration, advancement of future models that are more effective and precise. Moreover, it is advised to enhance the dataset by incorporating A variety of image samples representing different tooth characteristics and variations. This would improve the representativeness of the dataset and increase classification accuracy. Additionally, for future research, otential modifications to the layer classification segment of the architecture EfficientNet-B0 could be explored without compromising accuracy, precision, and recall.

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