Dental Diagnostics with Deep Learning: A VGG16-Based Approach for Classifying Segmented Dental Radiographs

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***Abstract*--- This research focuses on creating a deep learning architecture to categorise dental radiographs into categories such as Cavity, Fillings, Impacted Tooth, Implant, and Normal. Considerable preprocessing was carried out on the Dental Radiography dataset sourced from Kaggle. The dataset was pre-processed by segmenting individual teeth to allow the examination of specific dental conditions. The underlying architecture is a VGG16 convolutional neural network that has availed transfer learning in order to enhance the feature extraction capability. The dataset was divided into training, validation, and test sets, ensuring sufficient representation across all classes. In such a situation, it was able to obtain an overall accuracy of 96.52% on the test set with most classes having high precision and recall along with F1-score. Key findings give evidence of the effectiveness of deep learning for automation of diagnosis from radiographic images, while the VGG16 architecture is found particularly effective. Consequences implied by this research are that AI models can contribute a lot to dental professionals by making preliminary diagnoses faster and more accurately, hence improving diagnostic efficiency and patient care. This study thus holds importance in the sense that this will be one contributing factor to the emergent field of AI-assisted dental diagnostics, overcoming class imbalance problems and showing a possible clinical integration of deep learning models for better diagnosis.**

Keywords*: *Dental Imaging Classification, Deep Learning, CNNs, VGG16 Model, Advanced Dental Diagnostics.

I. INTRODUCTION

Dental diagnostics have dramatically evolved with the continuous development of imaging technologies, particularly with the change from 2D to 3D imaging modalities. It has revolutionized detecting and assessing dental situations by improving preciseness in diagnosis and, furthermore, patients' outcomes. The steps taken historically for dental radiography are summarized by Pauwels et al. [1] Modern imaging has become a vital tool in diagnosing dental caries, periodontal diseases, and periapical pathologies. Despite such advances, there are still numerous challenges to be met, especially with interpretation variability and the knowledge that manual analyses are exceedingly time-consuming. Artificial intelligence is bringing a paradigm shift in digital dental radiography, solving some of the long-standing problems. In the recent era, so many applications have adopted AI techniques for the automation of image analysis that may facilitate diagnosing with higher accuracy and may also clinically support decision-making. Putra et al. [2] discussed the use of AI in dentistry today, underlining potentials in improving efficiency and reducing errors. Deep learning, one of the important AI techniques in analyzing complex patterns of radiographic images, now performs with an unprecedented level of accuracy. With deep learning models, like CNNs, great potentials are imminent in dental diagnostics. The work by Endres et al. [3] illustrated the use of a CNN-based algorithm in the detection of periapical diseases from dental radiographs. These results underlined the model's reliability and accuracy, thus opening the doors toward more sophisticated AI tools in the clinic. Features extracted from the pre-trained models, such as VGG16, have risen to become literally indispensable in the continuing advance of diagnostic workflows by taking the next step in the classification and segmentation of dental images. The integration of digital radiography with biological agents beyond clinical diagnostics has extended its application to other areas, including human identification and forensic analysis. Yazdanian et al. [4] explored these interdisciplinary applications, illustrating the versatility of modern radiographic technologies. These advances underline not only the diagnostic potential of digital radiography but also the greater impacts it can have on healthcare and even beyond the field of medicine. Whereas traditional dental radiography has been quite instrumental in the detection of dental diseases over many years, as established by Douglass et al. [5], the incorporation of deep learning technologies heralds a quantum leap. Conventional methods are for the most part quite effective, but their limitations rest on dependence upon manual interpretation and clinicians' expertise. Deep learning-based approaches, especially those using models like VGG16, offer automation with high accuracy and reproducibility. This research will investigate the use of a deep learning algorithm based on VGG16 for classifying segmented dental radiographs. Advanced AI methodologies integrated with dental imaging allow this research to realize improvements in

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dental diagnostics, hence enhancing patient care and clinical outcomes.

II. Literature Review

Deep learning in dental radiography introduced new innings in dental diagnostics and classification. Recent works have established CNNs and other deep learning architectures as frontrunners in the race of automation of the diagnosis process, while many others proposed different techniques too. Bhat et al. [6] performed an extensive review on deep learning applications to dental radiograph analysis and brought out the role of CNNs in transforming dental diagnostics. They outlined the deep learning models, such as VGG16, ResNet, and EfficientNet, each capable of identifying and classifying dental diseases with high accuracy. The study also identified challenges such as the unavailability of annotated datasets and rigorous model evaluation metrics that are needed to normalize diagnostic workflows. Chauhan et al. [7] gave an overview of image processing methodologies, which are quintessential in dental diagnostics. The authors' research was focused on some of the preprocessing steps, such as enhancement of images, noise reduction, and segmentation, which can remarkably improve radiographs quality. In this paper, some techniques have been presented as preparatory steps for any deep learning model which optimizes input data in order to improve the accuracy of deep models in the detection of dental pathologies. Chen et al. [8] investigated a deep learning-based recognition system in order to identify periodontitis and dental caries within dental X-ray images. In that respect, they presented the results, which showed that the CNN-based models had a good sensitivity and specificity for the detection of these common dental conditions. This study further emphasized the potentials of such systems to aid clinicians in making good and timely diagnoses with minimal reliance on manual interpretation. Zhu et al. [9] conducted a pilot study on artificial intelligence use in panoramic radiograph analysis. Conclusion: They concluded that AI-based models indeed perform greatly in terms of detecting dental diseases such as caries, periodontitis, and impacted teeth. Their study was focused on the development and the use of panoramic radiographs combined with the deep learning algorithms that could give full information about conditions of oral health. Hasnain et al. [10] explored the contribution of using EfficientNet in dental radiography and how it had paramount results against X-ray image analysis in disease detection. Their study highlighted the scalable architecture of EfficientNet, elaborating on how this was conducive to high accuracy, reduced computational parameter spaces, and a balanced network scaling. These results have indeed substantiated that this model has been highly effective in enhancing diagnostic efficiency; thus, it is a very good model for clinical applications. Li et al. [11] applied YOLOv4 to the detection of tooth positions and dental anomalies on bitewing radiographs. Their study showed that this model is able to achieve state-of-the-art localization and classification of dental anomalies with great precision. It focused on the importance of object detection algorithms in orthodontics and restorative dentistry, where accurate identification of teeth is very important. Minoo and Ghasemi [12] presented a narrative review on the advancement of dental radiology using deep learning techniques. Their study focused on the shift from conventional diagnostic approaches toward AI-driven models, reflecting the increased accuracy and reliability of deep learning when interpreting complex radiographic images. They also highlighted that integration of the domain-specific dataset is necessary for the best performance of pre-trained models. Jacobs et al. [13] discussed the current role of radiographic diagnosis in periodontal diseases by comparing them with emerging innovations. They indicated the capability of AI models in providing enhanced diagnostic precision and monitoring of disease over time. Advanced imaging is, in turn, already combined with AI tools to cope with an increasing level of intricacy in periodontal diagnostics. Sadr et al. [14] executed a systematic review and meta-analysis regarding deep learning approaches for tooth classification and come to in dental radiography. Thereby, their investigation showed that deep learning algorithms adequately outperform classic techniques by offering a more accurate and reproducible identification of teeth across multiple modalities. Of course, standardization of these methods is highly needed for general clinical application. Conclusion Studies reviewed have shown how deep learning is affecting dental radiography in its full force and can change the face of diagnosis with automation and precision. These developments, ranging from disease detection to tooth identification, underline the additional value of high-level algorithms combined with imaging for enhanced diagnostics, smoothing clinical workflows.

III. METHODOLOGY

A. Data Collection and Data Preprocessing

The data collected for this study was obtained from the Kaggle. This one has detailed dental X-rays, which have been preprocessed for teeth segmentation, allowing examination of specific dental conditions like cavities, implants, fillings and impacted teeth. The dataset comprises 29,407 images distributed among the classes as follows: Cavity has 641 images; Fillings, 6,007; Impacted Tooth, 498; Implant, 2,047; and Normal, 20,214 images, as shown in Table I. This distribution suggests that the Normal class consists of the majority of the data set in the data distribution.

Table I. Image Distribution Among Dental Conditions

Class	Total
Cavity	641
Fillings	6007
Impacted Tooth	498
Implant	2047
Normal	20214

As a result, this balance may shift a bit leading to some overfitting and thus to counter this, data augmentation using the Keras ImageDataGenerator was used. Data enhancement involved scaling the pixel values, rotating up to 30 degrees, shifting up to 20% in width and height, shearing and zooming, changing brightness between 80% and 120%, flipping images horizontally, and filling in other neighboring pixel values for those created by augmentation. With the validation and the test data, only rescaling was done without any further augmentation to give a realistic evaluation on the model. Imaging was rescaled to a target size of 224*224 pixels required for VGG16 input. Data generators have been prescribed a batch size of 32 and the class mode was set to categorical because of the multiclass problem type. The pre-processing strategy would ensure that a variety and representative set of instances would get fed into the model

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for training, which would in the long run denominates the model as robust enough to classify several dental conditions from radiographic images, as seen in Fig 1.

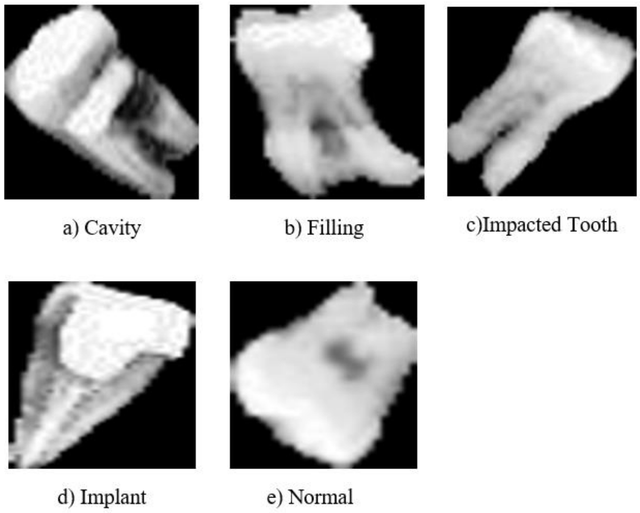

Fig. 1. Dataset Images for a) Cavity, b) Filling, c)Impacted Tooth, d) Implant, e) Normal

B. Data Splitting

Specifically, training, validation, and test data sets were accurately split to provide a comprehensive evaluation of the model's performance while using cross-validation techniques and random sampling for the purpose of avoiding overfitting the results. The CNN utilized a dataset of 29,597 images divided across five classes: Cavity, Fillings, Impacted Tooth, Implant, Normal was used as label stratification which were used to balance classes. The training class was 25,136, validation class was 2,812 and test class was 1,649, as shown in Fig 2.

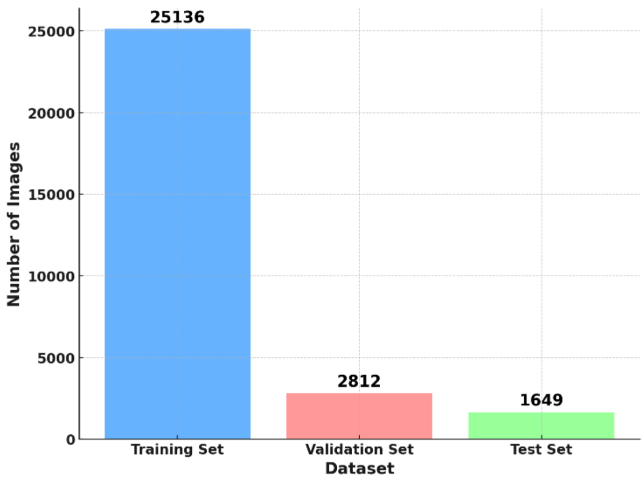

Fig. 2. Distribution of Training, Validation, Test Set

The distribution of images across different classes is as follows: Cavity comprised 576 training images, 43 validation images, and 22 testing images; Fillings included 5,242 training images, 540 validation images, and 315 testing images; Impacted Tooth had 428 training images, 38 validation images, and 32 testing images; Implant contained 1,784 training images, 159 validation images, and 104 testing images; Normal featured 17,106 training images, 2,032 validation images, and 1,176 testing images. Stratified splitting and preprocessing improved the classes' mutual availability and trained the model on balanced data, as shown in Fig 3.

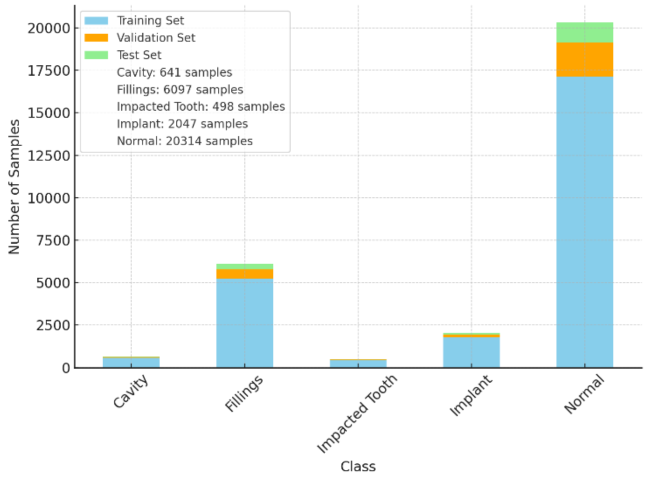

Fig. 3. Class-Wise Distribution of Images Across Training, Validation, and Test Sets

C. Model Selection and Architecture

The proposed convolutional neural network architecture in dental radiographs classification is VGG16, since it has appropriate efficacy with respect to image recognition tasks and the capturing of intricate features that might be present in medical images. VGG16 is a model characterized by a rather simple architecture but enhanced depth: convolutional layers follow each other, finally followed by fully connected ones. It has been initialized with pre-trained weights from ImageNet; this allows for the benefit of transfer learning, useful when working with limited medical image datasets. Some modifications were made to the network to create a new and better version of the VGG16 model for classifying dental radiographs, with only the final five convolutional layers being updated but the other layers were frozen. This is done in order for the model to still incorporate the pre-trained low level features in their network while it also trains other higher level features that can be useful to an image of teeth. Apart from that, a Global Average Pooling layer was included to downsample the feature maps along the spatial dimensions. Additionally, fully connected layers were constructed using the ELU activation function to learn features specific to dental pathologies. To prevent overfitting and enhance generalization, dropout and batch normalization layers were also incorporated. The final layer in the neural network employs softmax activation to assign images of dental to certain pre- defined classes. This deep architecture balances the depth of the information being measured and the computational cost of the final classification, as shown in Table II.

TABLE II. Summary of the Model Architecture

Layer Group	Layer Name (Type)	Output Shape	Parameters
Input	Input Layer	(None, 224, 224, 3)	0
Convolutional Base	VGG16 Pre-trained Layers:		
	Conv2D_1 (64 filters)	(None, 224, 224, 64)	1,792
	Conv2D_2 (64 filters)	(None, 224, 224, 64)	36,928

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	MaxPooling 2D_1	(None, 112, 112, 64)	0
	Conv2D_3 (128 filters)	(None, 112, 112, 128)	73,856
	Conv2D_4 (128 filters)	(None, 112, 112, 128)	147,584
	MaxPooling 2D_2	(None, 56, 56, 128)	0
	Conv2D_5 (256 filters)	(None, 56, 56, 256)	295,168
	Conv2D_6 (256 filters)	(None, 56, 56, 256)	590,080
	Conv2D_7 (256 filters)	(None, 56, 56, 256)	590,080
	MaxPooling 2D_3	(None, 28, 28, 256)	0
	Conv2D_8 (512 filters)	(None, 28, 28, 512)	1,180,160
	Conv2D_9 (512 filters)	(None, 28, 28, 512)	2,359,808
	Conv2D_10 (512 filters)	(None, 28, 28, 512)	2,359,808
	MaxPooling 2D_4	(None, 14, 14, 512)	0
	Conv2D_11 (512 filters)	(None, 14, 14, 512)	2,359,808
	Conv2D_12 (512 filters)	(None, 14,14 ,512)	2.359.808
	Conv2D_13 (512 filters)	(None ,14 ,14 ,512)	2.359.808
	MaxPooling 2D_5	(None ,7 ,7 ,512)	0
Custom Head	Additional Layers:		
	GlobalAvgPool (GlobalAveragePooling2D)	(None ,512)	0
	Dense_1 (256 units, ReLU)		(None ,256)
	Dropout_1 (rate=0.5)		(None ,256)
	Dense_2 (256 units, ReLU)		(None ,256)
	Dropout_2 (rate=0.5)		(None ,256)
	Dense_3 (64 units, ReLU)		(None ,64)
	BatchNorm_1(BatchNormalization)		(None ,64)
	Output_Layer(Dense , Softmax activation)		

D. *Training Process*

In the classification of space of dental radiographs, a CNN architecture such as VGG16 was used. It has been demonstrated that the method is highly effective for image recognition and consequently it can reveal various characteristics of any picture of a medical nature. The VGG16 is a model that is easily to describe but has deep architecture that encompasses simple sequential convolutions with fully connected layers. It was initialized with learned weights from ImageNet to take advantage of the transfer learning which is quite helpful especially when working with a small set of medical images. When implementing the VGG16 network on a dental radiograph classification task, all but the last five convolutional layers were fixed in this study. This could enable the model to carry over to learn low level features from the features in the pre-trained network and also tune for higher level features presumably relevant for the dental images. Fully connected layers were included with ELU activation since it makes sense to include them and learn specific patterns related to dental pathologies, dropout and batch norms were used to correct for overfitting. The last output layer classification contains a softmax activation function to categorize the kinds of images into official dental categories. These architectures balance depth and computational requirement well so that they can perform classification of dental radiographs with reasonable efficiency and accuracy.

E . *Evaluation*

After training the model with the VGG16-based approach, several standard metrics for evaluating the performance of this classifier were implemented one after another: especially, accuracy, precise, recall, the F1 threshold, and confusion matrix measurements. This will be done in order to familiarize with a comprehensive comprehension of the model in terms of its ability to classify different dental conditions from the radiographic images.

Fig. 4. Methodology Proposed in This Study

IV. RESULTS

A. *Comparison for Training and validation loss*

Training loss decreased linearly from 1.3714 in Epoch 1 to 0.0462 at the end of Epoch 7, reflecting the gain in the model's capabilities of reducing errors while learning. It had the minimum value of 0.1227 in Epoch 4 for the validation loss, which corresponds to the maximum value of 96.28% for validation accuracy. The increase in validation loss after Epoch 4, while training loss was still dropping, gives evidence of overfitting. These further cements the fact that both metrics have to be watched out for during training to avoid overfitting. The early stopping mechanism helped to stop the training quite before a serious degradation within the validation performance kicked in. The training and validation losses in the initial epochs are almost similar, which shows that the model is ideal for real classification tasks. Based on numerous epoch and confined training and validation losses, a comprehensive analysis of loss metrics is essential, as depicted in Fig 5.

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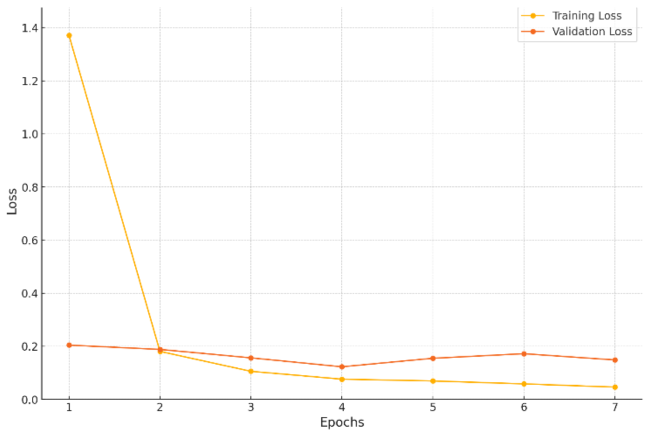

Fig. 5. Training and validation loss

B. Comparison for Training and Validation Accuracy

The training accuracy improved over the epochs from 62.62% in epochs 1 to 98.58% from epochs 7 as a sign that the model learnt a lot from the training data. Similarly, at the beginning, the validation accuracy was quite high, starting at 93.39% at Epoch 1 and peaking at 96.28% in Epoch 4, copying quite well with data not seen. There was, however, a slight deterioration in validation accuracy after Epoch 4, probably a consequence of overfitting by the model in its continued optimization on the training data. These results must clearly show the high generalization ability of the model, which therefore makes it appropriate for real-world applications with similar databases, as shown in Fig 6.

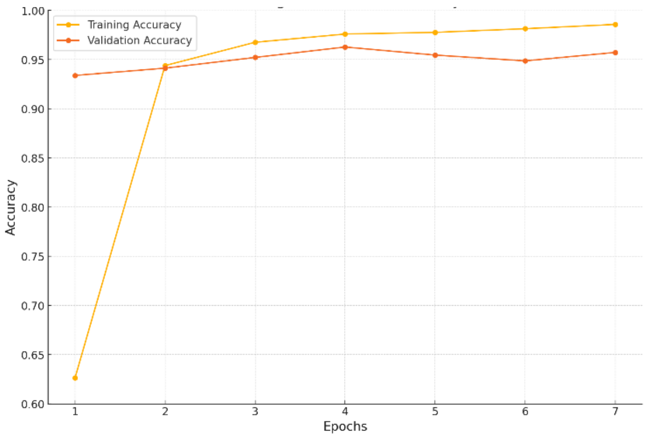

Fig. 6: Training and Validation Accuracy

C. Evaluation of the Confusion Matrix

Overall model performance in classifying the dental conditions can be well understood from the confusion matrix that provides the actual and predicted values. The corrected classified elements are along the diagonal, and high values mean the model predicted many instances correctly. For a class like "Cavity", "Fillings", "Impacted Tooth", and "Normal", it is doing a very good job, per se, considering that very few misclassifications occur in other classes. However, there are many “Normal” cases wrongly clustered into “Implant”, which may indicate that the features of implants can sometimes be almost indistinguishable from normal tissue structures in dental radiographs. It could be attributed to resemblance in the radiographic appearances or possibly insufficient discriminating features being taught to the model for these classes. However, the confusion matrix suggests that there are issues in the discrimination in the “Implant” and “Normal” classes whereby means that there is a need to either increase the number of images of the implants or work on the feature extraction methods to identify the features of implants, as illustrated in Fig 7.

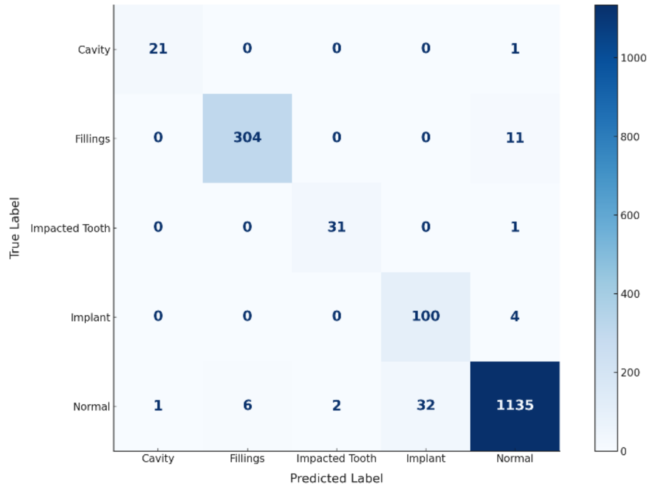

Fig. 7. Confusion Matrix Depicting Classification Performance

D. Classification Report Analysis

The evaluation report provides an outlook for all classes using precision, recall, and F1-score of the model. Precision and recall greater than 93% for maximum of the classes were obtained, showing a high level of positive cancer identification with minimal false negative and false positive results. For example, precision and recall values of 96% and 97% respectively were recorded for “Cavity” and “Fillings” classes to show the robustness of the proposed model in identifying these conditions. The same applies to the “Impacted Tooth” class that seems to deliver good results with fairly equal measures of precision and recall. However, the “Implant,” class reveals a slightly lower accuracy of approximately 75.76 %; thus, it is likely to identify other body conditions as imprints. This influences the F1-score of “Implant” though not very high; it is lower than those recorded for the other classes. In the macro level, leaving at an average F1-score level of 94.48% and a weight per class average F1-score of 96.66% reveals that overall performance is general, but classification stability varies from one class to the other. In this context, the report demonstrates that the studied model performs well and suggests improving the ‘Implant’ class by further data extension or some modifications in the training approach, as shown in Table III.

TABLE III: Classification Metrics Report

Class	Precision (%)	Recall (%)	F1-Score (%)	Support
Cavity	95.45	95.45	95.45	22
Fillings	98.07	96.51	97.28	315
Impacted Tooth	93.94	96.88	95.38	32
Implant	75.76	96.15	84.81	104
Normal	98.52	96.51	97.50	1,176
Overall Accuracy			**96.52%**	1,649
Macro_Avg	92.35	96.30	94.48	1,649
Weighted_Avg	96.98	96.52	96.66	1,649

V. CONCLUSION

The following paper provides development and tuning of the VGG16 CNN model to enable classification into five classes. Its overall test accuracy came at the high value of

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96.52%, hence becoming pretty effective in identifying various dental conditions from radiographic images. Precision, recall, and F1-score are common metrics and show very good performance on most of the classes, especially "Cavity", "Fillings", and "Impacted Tooth"; this eventually meant that in such circumstances, the model was reliable when one wanted to diagnose those conditions. It showed a relatively lower precision in the "Implant" class, which indicated further refinement in the classifier so as to avoid misclassifications that may have arisen from the feature overlap with normal dental structures. These results show that deep learning models have a promising future to support dental experts in providing fast and accurate preliminary screenings of dental radiographs, which will enhance diagnostic efficiency and improve patient care. Future work could include increasing the number of images in the dataset, particularly for underrepresented classes, in hopes of improving the model's ability to generalize. Still, better results could be achieved using advanced architecture or ensemble methods if applied. Attention mechanisms can be used to help the model focus on more relevant areas of the image, further enhancing class discrimination. To further promote the dissemination of this type of technology as a viable tool in dental diagnosis, there would also be the need for clinical confirmation of the proposed model, in addition to opinions from practising dentists.

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