Deep Learning-based Evaluation Of The Relationship Between Mandibular Third Molar And Mandibular Canal On CBCT

1215R
PROJECT ID

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OVERVIEW

The aim of this project is to address the issue of class imbalance in dental diagnostic datasets by utilizing Generative Adversarial Networks (GANs) in conjunction with CNN models, namely VGG-16 and ResNet-50. The purpose of this integration is to enhance precision in the detection of dental problems using CBCT images. In the future, we intend to improve our strategy by utilizing the knowledge we have acquired, by applying other data augmentation method. This will facilitate further progress in dental diagnostics.

OBJECTIVES

1. Imbalance Mitigation: Fix the dataset's class imbalance to improve model training.
2. Generative Adversarial Network (GAN) Integration: Using GAN to generate synthetic images to correct the imbalance.
3. Model Enhancement: Integrate GAN-augmented data into existing CNN models.
4. Performance Evaluation: Extract insights into the effectiveness of the GAN-augmented CNN models.

PROBLEM STATEMENTS

The current challenge is to solve the imbalance among data classes in our dataset, which hinders the effectiveness of our Convolutional Neural Network (CNN) models, particularly VGG-16 and ResNet-50. The imbalance distribution of classes negatively affects the models' capacity to precisely detect dental problems in Cone Beam Computed Tomography (CBCT) images.

Distoangular

L: 20 images
R: 21 images

Horizontal

L: 79 images
R: 84 images

Mesioangular

L: 72 images
R: 71 images

Transverse

L: 2 images
R: 4 images

Vertical

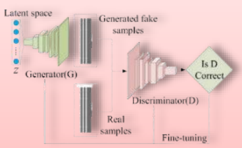
L: 160 images
R: 140 images

DATASETS & CNN MODELS

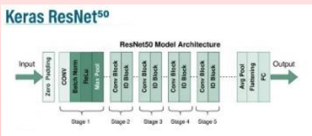
1. There are 2 main datasets, which are the left and right side of the CBCT images of mandibular third molar. Each has 5 subclasses, namely *distoangular, horizontal, mesioangular, transverse and vertical.*
2. Mandibular third molar, commonly known as the "lower wisdom tooth," is the third molar located in the mandible, which is the lower jaw.
3. Compared to VGG19, VGG16 has fewer parameters, which can contribute to reduced overfitting.
4. Resnet50 provides a good compromise between model accuracy and computational efficiency, compared to other Resnet models.

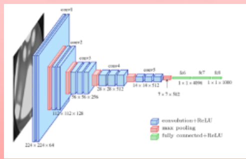
METHODOLOGY

GAN Architecture



Resnet-50 Architecture





VGG-16 Architecture

Tools used

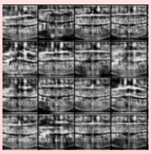
- The datasets were obtained from IIUM Kuantan.
- The data is then being augmented to balance out the number of images throughout the datasets. with a total of 200 images for each class.

RESULTS & DISCUSSION

Real vs Generated Images via GAN

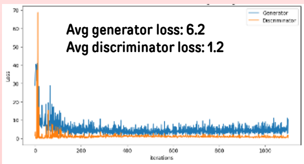
Real Images

VS



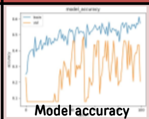
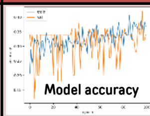
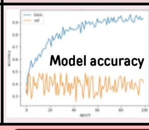
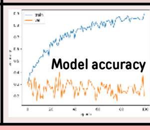
Generated Images

Evaluation Metrics of GAN



Generator & Discriminator loss after 100 epochs

Evaluation Metrics of CNN Models B&A Implementation of GAN

	Before (100 epochs)		After (100 epochs)	
Res - Net 50	 Model accuracy	Accuracy: 0.46 Train loss: 5.77 AUC: 0.67	 Model accuracy	Val accuracy: 0.40 Train accuracy: 0.39 Val loss: 217.18 Train loss: 215.24 AUC: 0.63
VGG - 16	 Model accuracy	Accuracy: 0.40 Train loss : 0.8 AUC: 6.6	 Model accuracy	Val accuracy: 0.33 Train accuracy: 0.98 Val loss: 1.62 Train loss: 0.2 AUC: 0.69

Discussion

Resnet50

1. Increased in train & val loss, which means that the model is not fitting well into the training data.
2. Decreased in training accuracy, means that it is not predicting the generated images that well.

VGG16

1. Increased in val loss, which indicates a bad generalization of new data.
2. Increased in train accuracy but decreased in val accuracy, this indicates an overfitting.

Key

Val accuracy: higher the better
Train accuracy: higher the better
Val loss: lower the better
Train loss: lower the better

Conclusion

The results worsened due to GAN implementation; it is better to use real images only.

FUTURE WORKS

1. Implement another image classification model such as Pix2Pix and CycleGAN.
2. Use bigger image size during training and testing. From 128 x 128 pixels to 300 x 300 pixels or more. Downscaling images might lose the vital features. of the images as the number of pixels are significantly reduced.
3. Use different types of CNN model such as ResNet101 ,VGG19 and DenseNet.

References

1) ukegawa, S., Tanaka, F., Hara, T., Yoshii, K., Yamashita, K., Nakano, K., Takabatake, K., Kawai, H., Nagatsuka, H., & Furuki, Y. (2022). Deep learning model for analyzing the relationship between mandibular third molar and inferior alveolar nerve in panoramic radiography. Scientific Reports, 12(1). https://doi.org/10.1038/s41598-022-21408-9
2) Liu, M., Xu, Z., Mao, W., Li, Y., Zhang, X., Bai, H., Ding, P., & Fu, K. (2021). Deep learning-based evaluation of the relationship between mandibular third molar and mandibular canal on CBCT. Clinical Oral Investigations, 26(1), 981–991. https://doi.org/10.1007/s00784-021-04082-5

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