

Correlation between image quality measurement of different image enhancement algorithms and Cascade R-CNN detection results applied to teeth detection in panoramic X-Ray images

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Automatic teeth detection and segmentation in dental radiographs play a significant part in forensic identification and are considered the first step towards more complex systems for oral healthcare [3]. The reading and interpretation of X-ray images are time-consuming tasks, mainly performed by dentists where misdiagnosis can occur due to inexperience, fatigue or professional bias [3]. Numerous computer-assisted systems have been proposed to reduce the workload of professionals. Indeed, most of the published work based on Neural Networks (NN) focuses on tooth detection and segmentation, some of them achieving results above 90% [5]. In this work, we applied different image enhancement techniques as a pre-processing step to determine which features of the image are correlated to a better detection performance of teeth in panoramic images using an object detection algorithm. We used Cascade NN [2] for training 5 models, one trained with the original dataset and 4 trained with the dataset obtained after the application of different image enhancement techniques. The scheme can be seen in Figure 1 A). The images used to train the models belong to a publicly available dataset of 1500 images [6], of which 300 were annotated and validated by professionals dentists.

The 300 images were split into 192 for training, 48 for validation, and 60 for testing. The image enhancement techniques considered were the smoothing-edge preservation filters Anisotropic Diffusion [1], Bilateral Filtering [1], and the contrast enhancement algorithms BBHE [4] and QHELC [4]. Each model was trained for 8 epochs, with a learning rate of 0.009 and a batch-size of 2 in Google Colab. We evaluated the results considering the image processing outcome and the detection performance. For evaluating the image enhancement, we considered quality metrics like SSIM, PSNR, Edge Preservation Index (EPI), global contrast and Contrast Improvement Ratio (CIR) [4]. Whereas the detection performance was evaluated by measuring the accuracy, precision, and recall after considering as true detection those teeth that present bounding boxes with an IoU ≥ 0.5 . Table 1 shows the scores achieved by each model. Applying QHELC presents the best detection performance since it slightly increases the global contrast and preserves the main features of the

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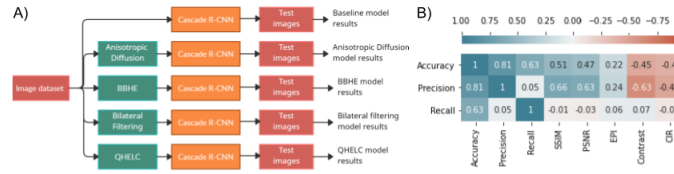


Figure 1: A) Experimental pipeline overview. B) Correlation heat map.

images, which translate to a high SSIM value. On the contrary, applying BBHE doubles the global contrast and raises the local contrast significantly, also producing a low PSNR, in detrimental of detection performance.

Table 1: IQM of the testing group. Accuracy, precision and recall of the models.

	(IQM)					Models' performance trained with IQM		
	SSIM	PSNR	EPI	Contrast	CIR	Accuracy (%)	Precision (%)	Recall (%)
Original				33.12		99.43	99.94	99.49
Anisotropic diffusion	0.963	41.003	0.423	32.71	0.742	99.37	99.89	99.49
BBHE	0.710	14.810	0.423	74.15	39.204	95.35	95.76	99.54
Bilateral Filtering	0.970	42.996	0.448	32.86	0.680	99.37	99.94	99.43
QHELC	0.993	36.906	0.913	36.33	0.188	99.49	99.94	99.54

We compute the cross-correlation between the performance of the detection models and the Image Quality Metrics (IQM) measured per image. Figure 1 B) shows that accuracy and precision have a negative relation with the global contrast and CIR, which means that significantly increasing the global and local contrast of the original images would negatively affect the detection performance metrics. On the other hand, detection performance would increase if the image presents less distortion and noise, as shown by the positive correlation with SSIM and PSNR.

References

- [1] Barash. D. Bilateral Filtering and Anisotropic Difusion: Towards a Unified Viewpoint, *Scale-Space and Morphology in Computer Vision*, volume 2106, 2001. DOI: 10.1007/3-540-47778-0-24.
- [2] Cai, Z. and Vasconcelos, N. Cascade R-CNN: High Quality Object Detection and Instance Segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 43:1483–1498, 2019. DOI: 10.1109/TPAMI.2019.2956516
- [3] Chen, H., Zhang, K., Lyu, P., Li, H., Zhang, L., Wu, J. and Lee, C. A deep learning approach to automatic teeth detection and numbering based on object detection in dental periapical films, *Scientific Reports*, 9, 2019. DOI: 10.1038/s41598-019-40414-y.
- [4] Mello, J. C., Fretes, V. R., Adorno, C. G., Gariba, R. Vázquez, J. L., Legal-Ayala, H., Mello-Román, J. D., Escobar, R. D. and Facon, J., Panoramic Dental Radiography Image Enhancement Using Multiscale Mathematical Morphology, *Sensors*, 21, 2001. DOI: 10.3390/s21093110.
- [5] Schwendicke, F., Golla, T., Dreher, M. and Krois, J. Convolutional neural networks for dental image diagnostics: A scoping review, *Journal of Dentistry*, 91, 2019. DOI: 10.1016/j.jdent.2019.103226.
- [6] Silva, G, Oliveira, L., and Pithon, M. Automatic segmenting teeth in X-ray images: Trends, a novel data set, benchmarking and future perspectives, *Expert Systems with Applications*, 107:15–31, 2018. DOI: 10.1016/j.eswa.2018.04.001.