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# Image Processing for Tooth Type Classification using Deep Learning

## Derin Öğrenme Kullanılarak Diş Tipi Sınıflandırması için Görüntü İşleme

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**ABSTRACT**

**Objective:** Tooth classification is a crucial aspect of dentistry, influencing effective diagnosis, treatment planning, and overall oral health. However, the subjectivity and variations in human judgment, coupled with the complexity of dental conditions, have led to disparities in tooth classification, particularly in cases involving multiple dentists' opinions, varying clinical expertise, and differing dental standards. Recent advances in technology and artificial intelligence have created new opportunities for innovative solutions in tooth classification. This paper aims to investigate the effect of image processing techniques on classification performance of teeth using deep learning. 4 classes - Incisor, Canine, Premolar, Molar- from panoramic radiographs are prepared.

**Methods:** The state-of-the-art 6 deep learning classification models -Xception, GoogleNet, ResNet18, ShuffleNet, MobileNetV2, ResNext50- was implemented with transfer learning for model efficiency. Two models with the highest and lowest performance were chosen for further analysis related to image processing. 10 different image processing techniques (Gaussian Noise, Gaussian Blur, Wavelet Transform, Sharpness, Contrast Enhancement, Color Correction, Elastic Transform, Random Erasing, Local Binary Patterns, Local Max Min) were applied to these two models.

**Results:** The Xception provided the highest accuracy of 90.25% while ResNet18 yielded the lowest accuracy of 74.86%. Additionally, findings indicated that certain image processing techniques can improve classification performance.

**Conclusion:** The present work shows that image processing can enhance automated artificial intelligence-based solutions for more robust tooth classification, with the potential to improve dental diagnosis and treatment planning.

**Keywords:** Dentistry, classification, deep learning, artificial intelligence, radiography

**ÖZ**

**Amaç:** Diş sınıflandırması, etkili tanı, tedavi planlaması ve genel ağız sağlığını etkileyen diş hekimliğinin önemli bir yönüdür. Ancak, insan yargısındaki öznellik ve farklılıklar, diş koşullarının karmaşıklığıyla birleşince, özellikle birden fazla diş hekiminin görüşünü, farklı klinik uzmanlıkları ve farklı diş standartlarını içeren vakalarda diş sınıflandırmasında farklılıklara yol açmıştır. Teknolojideki ve yapay zekadaki son gelişmeler, diş sınıflandırmasında yenilikçi çözümler için yeni fırsatlar yaratmıştır. Bu makale, derin öğrenme kullanarak görüntü işleme tekniklerinin dişlerin sınıflandırma performansı üzerindeki etkisini araştırmayı amaçlamaktadır. Panoramik radyografilerden 4 sınıf - Kesici, Köpek, Küçük Azı, Azı - hazırlanmıştır.

**Yöntemler:** Son teknoloji 6 derin öğrenme sınıflandırma modeli -Xception, GoogleNet, ResNet18, ShuffleNet, MobileNetV2, ResNext50- model verimliliği için transfer öğrenmesiyle uygulandı. Görüntü işlemeyle ilgili daha fazla analiz için en yüksek ve en düşük performansa sahip iki model seçildi. Bu iki modele 10 farklı görüntü işleme tekniği (Gaussian Noise, Gaussian Blur, Wavelet Transform, Sharpness, Contrast Enhancement, Color Correction, Elastic Transform, Random Erasing, Local Binary Patterns, Local Max Min) uygulandı.

**Bulgular:** Xception %90,25'lik en yüksek doğruluğu sağlarken ResNet18 %74,86'lık en düşük doğruluğu sağladı. Ek olarak, bulgular belirli görüntü işleme tekniklerinin sınıflandırma performansını iyileştirebileceğini gösterdi.

**Sonuç:** Mevcut çalışma, görüntü işlemenin daha sağlam diş sınıflandırması için otomatik yapay zeka tabanlı çözümleri geliştirebileceğini ve diş teşhisini ve tedavi planlamasını iyileştirme potansiyeline sahip olduğunu göstermektedir.

**Anahtar Kelimeler:** Diş hekimliği, sınıflandırma, derin öğrenme, yapay zeka, radyografi

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## INTRODUCTION

Tooth classification is the process of categorizing teeth based on their location, function, shape, and other characteristics. This classification system helps dentists and dental professionals communicate effectively about specific teeth and their properties. Instead of conventional approach, automated tooth recognition offers advantages in terms of accuracy, consistency, speed, and the ability to generate data, especially towards digital dentistry.

Deep learning plays a significant role in tooth classification, a critical task in various fields such as dentistry, orthodontics, and forensic odontology including other applications in medicine.[1-5] Deep learning techniques, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have revolutionized this process by automating and improving the accuracy of tooth classification tasks.

Image processing is a field of study that involves manipulating and analyzing digital images using various techniques and algorithms. It encompasses a wide range of operations to enhance, compress, or extract information from images. Some common image processing tasks include blurring, sharpening, image compression and noise reduction to improve image quality or extract specific features.

This work aims to investigate the effectiveness of image processing techniques on the automated classification performance of teeth using deep learning on panoramic radiographs. In the first phase, the state-of-the-art 6 deep learning classification models are implemented with transfer learning for model to compare model performances. Two models are determined with the highest and the lowest performance, which are later used to investigate the effect of various image processing techniques. In the second phase, images are individually processed by 10 different image processing techniques. Processed images are then applied to the two models chosen to evaluate the effect of image processing techniques on classification performance.

## METHODS

*Data Preparation*

Panoramic images used in this work are taken from a public open-access dataset, The Tufts Dental Database.[25] Informed Consent form and Ethics Committee Approval are not needed due to the use of public anonymous dataset. Teeth with any restoration (filling, crown, endodontic treatment, etc.), teeth with any tooth-related pathology or anomaly, and images with artifacts with unclear borders were excluded. Tooth types are prepared based on 4 classes, namely incisor, canine, premolar, molar among 1000 panoramic radiographs. There are 10876 cropped images in total: 3176, 1621, 2745 and 3334 cropped images for each class- incisor, canine, premolar, molar- respectively.

*Classification using Deep Learning*

There are 6 different the state-of-the-art deep learning models implemented in this work for classification. They are Xception, GoogleNet, ResNet18, ShuffleNet, MobileNetV2, and ResNext50. An open source machine learning framework, PyTorch, is used to implement the models with batch size of 32, learning rate 0.1, cross entropy loss function. They are briefly explained as follows.

*Xception* is a deep learning model, the abbreviation of "Extreme Inception," which stands for "Concentrated Convolution" to achieve results. Developed by Google, this model belongs to the family of Convolutional Neural Networks (CNN) and demonstrates successful performance, particularly in image processing tasks.[6] Xception is designed as an improved version of the original Inception model, using concentrated convolution operations to build a deep learning network. This model is widely employed for image classification, object recognition, and other visual tasks.

*GoogleNet,* also known as Inception-v1, is an innovative Convolutional Neural Network (CNN) model developed by Google, introduced in a 2014.[7] This model's uniqueness lies in its pioneering approach to structuring deep networks using "Inception" modules, which allow for the simultaneous utilization of convolution filters of varying sizes, facilitating the learning of a multitude of feature maps and thereby enabling deeper networks to learn more effectively. GoogleNet has been widely recognized for its high accuracy on large datasets like the ImageNet Large Scale Visual Recognition Challenge, and its complex architecture, comprising numerous convolutional and fully connected layers, has made it a preferred choice for various visual processing tasks when used in conjunction with other deep learning models.

*ResNet-18* is a deep learning model, specifically used for image classification tasks based on the principle of "residual learning," enabling the network to become deeper and more complex.[8] ResNet-18 is designed with a depth of 18 layers and facilitates information transfer with "skip connections" known as "residuals" before each layer. This architecture provides sufficient performance for a wide range of image processing tasks, except for tasks that require larger and more complex ResNet variants. It is particularly popular in transfer learning applications.

*ShuffleNet* is a lightweight and cost-effective Convolutional Neural Network model designed primarily for visual recognition and computer vision applications.[9] It aims to reduce the complexity and computational cost of models like Inception and ResNet. ShuffleNet achieves this by employing specialized techniques such as "group convolutions" and "channel shuffling" to shrink its size, making it an ideal choice for resource-constrained devices and fast object recognition applications. It efficiently delivers performance in applications that require low-cost and lightweight models, particularly serving as a preferred solution for smartphones and other resource-limited devices.

*MobileNetV2* is a lightweight Convolutional Neural Network model designed for resource-constrained platforms, particularly mobile devices and embedded systems to perform visual processing tasks like object detection and classification rapidly and efficiently.[10] MobileNetV2 employs depth wise separable convolutions to reduce model complexity and use computational resources more effectively.

*ResNeXt-50* is a variant of Residual Next and is a convolutional neural network model designed for visual classification, object detection, and various other visual tasks.[11] It is part of the Residual Next (ResNeXt) family and uses the concept of "cardinality" to increase information extraction capacity with more parallel pathways and a wider channel count. ResNeXt-50 comprises 50 layers and typically delivers high performance, especially when combined with other deep learning models, on a broader dataset.

*Image Processing Techniques*

Image preprocessing techniques are employed to improve the quality of the input images and make them more suitable for deep learning models. They help prepare, clean, and optimize the input data, improving the model's performance, robustness, and ability to learn from the data effectively. 10 image processing techniques are used in this work, and they are briefly explained as follows.

*Gaussian Noise* is a statistical type of noise used as an image processing and enhancement technique. This type of noise is applied by adding random values with a normal (Gaussian) distribution to random pixels in an image. In this study, different levels of Gaussian Noise (std: 10, 20) were added to radiographic images. These levels were meticulously chosen for the comparability and repeatability of the experiments.

*Gaussian Blur* is a process that smoothens an image, softening the details within it. This operation is employed to reduce noise, enhance sharpness, and improve the overall quality of images. In this study, Gaussian Blur was applied with different Sigma (σ: 2, 10) values, where higher σ values result in more pronounced blurring.

*Wavelet Transform* is a process used to analyze an image at different scales and extract essential features. This operation examines the frequency components in images and recognizes wave patterns. In this study, different Wavelet Transform filters (Db2, Db6) were applied to the image. This process was employed to emphasize features in dental radiographs and enhance classification accuracy.

*Sharpness* is a process used to accentuate edges and details in an image, resulting in a crisper and clearer appearance. Different sharpness levels (2, 5) were applied to the images in this study.

*Contrast Enhancement* is a process used to increase the contrast of an image, making it appear better and more visually appealing. This operation adjusts the color tones in images and enhances contrast. Different contrast levels (0.5, 1.8) were applied to improve the contrast of the images in this study.

*Color Correction* is a process used to correct the color balance of an image, making colors appear more accurate and realistic. This operation adjusts the saturation, brightness, and color tones of images. Different levels of color correction (saturation: 5, 50) were used to enhance the colors of the images.

*Elastic Transform* is a process used to simulate the elastic deformation of an image. This operation involves deformations such as stretching, shrinking, and rotating the images. Different Alpha values (alpha: 10, 50) were used to apply elastic transformation to the images.

*Random Erasing* is a process that increases data diversity by randomly erasing a portion of an image. This operation obscures specific areas of the images with a probability of random erasure. Different p (probability of applying random erasing) values (p: 0.3, 0.8) were used to apply random erasure to the images.

*Local Binary Patterns* is a process that divides an image into small local regions and describes the unique patterns within these regions. This operation is used to capture texture information in images. In this study, different interpolation methods (Bilinear, Nearest, Bicubic) were used to extract local binary patterns from the images. The Local Binary Patterns operation was applied to identify textural features in dental radiographs and improve classification performance.

*Local Max Min* is a process that computes the local pixel values within an image. This operation is used to identify and emphasize local extrema in the image. In this study, different threshold values (threshold: 0.3, 0.7) were used to calculate local maximum and minimum values in the images. The Local Max Min operation was applied to extract local pixel values in dental radiographs and enhance the features.

First, 6 state-of-the-art deep learning classification models were applied in combination with transfer learning to compare model performances. The two models with the highest and two with the lowest performance were then identified to be used to investigate the effect of various image processing techniques. In the second stage, the images were processed individually with 10 different image processing techniques. The processed images were then applied to the two selected models to evaluate the impact of image processing techniques on classification performance.

## RESULTS

In this section, the results of model comparisons and the outcomes of the various image processing and enhancement techniques applied were presented. Firstly, models were trained and their performance was given in Table 1. Accuracy for each model referred to the average accuracy value obtained for 4 classes. It spans between 0.74 and 0.90.

**Table 1.** Accuracy for each model

| *Model* | *Accuracy* |
|---|---|
| Xception | **0.90** |
| GoogleNet | 0.88 |
| ResNet18 | **0.74** |
| ShuffleNet | 0.85 |
| MobileNetV2 | 0.76 |
| ResNeXt-50 | 0.87 |

The best and the lowest performance were yielded by Xception and ResNet18. They were selected to be used for further analysis regarding image processing techniques. Image processing techniques were individually applied to the image dataset. Then, processed images were used to train models. Table 2 showed performances of these two models based on the image processing techniques applied.

**Table 2.** Performances of Xception and ResNet18 for the image processing techniques applied

| Processing Techniques | | Xception (Acc) | ResNet18 (Acc) |
|---|---|---|---|
| Gaussian Noise | std: 10 | 0.89 | 0.72 |
| | std: 20 | 0.88 | 0.71 |
| Gaussian Blur | sigma: 2 | 0.89 | 0.70 |
| | sigma: 10 | 0.89 | 0.70 |
| Wavelet Transform | db2 | **0.91** | **0.78** |
| | db6 | 0.86 | 0.72 |
| Sharpness | level-2 | 0.88 | 0.71 |
| | level-5 | 0.89 | **0.79** |
| Contrast Enhancement | level 0.5 | 0.88 | 0.70 |
| | level 1.8 | 0.89 | 0.75 |
| Color Correction | sat: 5 | 0.88 | 0.68 |
| | sat: 50 | 0.89 | **0.81** |
| Elastic Transform | sigma: 10 alpha: 50 | 0.88 | **0.80** |
| Random Erasing | p: 0.3 | 0.89 | **0.77** |
| | p:0.8 | 0.89 | 0.70 |
| Local Binary Patterns | bilinear | 0.89 | 0.66 |
| | nearest | 0.88 | 0.74 |
| | bicubic | 0.87 | **0.84** |
| Local Max Min | threshold: 0.3 | 0.89 | 0.70 |
| | threshold: 0.7 | 0.88 | 0.67 |

It was seen that the Xception model showed approximately similar performances after the applied image processing applications. Only the Wavelet Transform method outperformed the default performance. On the other hand, the ResNet18 model performed up to 13% better than the first case with various parameters of Wavelet Transform, Sharpness, Color Correction, Elastic Transform, Random Erasing and Local Binary Patterns methods

## DISCUSSION

Deep learning has emerged as a powerful tool in the field of dental classification processes, revolutionizing the way dental professionals diagnose and categorize various oral conditions. Leveraging complex neural networks and large datasets, deep learning algorithms have the capacity to analyze dental images and radiographs with remarkable accuracy, helping to identify and classify a wide range of dental issues such as caries, periodontal diseases, and tooth anomalies.[12-20] This transformative technology not only enhances the speed and precision of diagnoses but also holds the potential to streamline treatment planning and improve patient care, making it a promising asset in the ever-evolving landscape of dental healthcare.

Upon a thorough review of existing literature, it is noteworthy that extant studies have addressed tooth classification; however, it is imperative to observe that comprehensive investigations concerning the impact of image processing methods within this domain have yet to be encountered. Additionally, considering different types of images and evaluation metrics reported, it is difficult to make a direct comparison. The findings in the present work investigated the role of image processing techniques on classification performance of different tooth types. It shows that there is a potential to improve classification performance of deep learning models by carefully choosing and applying image processing technique.

Previously, Li et al.[21] applied deep convolutional neural network to identify teeth types of 4 classes, reported average sensitivity of 0.87. Sukegawa et al.[22] classified mandibular third molars using VGG16 convolutional neural network using cropped images of panoramic radiographs, providing accuracy between 0.77 and 0.88. Estai et al.[23] segmented permanent teeth on 591 orthopantomogram using deep learning, resulting in intersection over union score of 0.70. Krois et al.[24] studied cropped tooth image context up to 300% scaling from panoramic radiographs using ResNet34, resulting significant improvement in accuracy.

Several limitations need to be stated, firstly there is a lack of large, balanced open access dental datasets for benchmarking, secondly there is no consensus in reporting findings in the literature, which should be considered for developing robust models before clinical integration.

To conclude, this study demonstrates that deep learning models are promising tools to effectively classify tooth types with high accuracy. Image processing techniques in general have the capacity to enhance classification performance. There is still room to handle limitations towards clinical integration for daily use.

**Ethics Committee Approval:** Panoramic images used in this work are taken from a public open-access dataset, The Tufts Dental Database. Ethics Committee Approval are not needed due to the use of public anonymous dataset.
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