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LİSANS TEZİ

PANOREX.AI

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Her hakkı saklıdır

**TEZ ONAYI**

**Muhammed Tekin ve Mustafa Kaya Bozbel** tarafından hazırlanan " **Panorex.ai** " adlı tez çalışması **14/06/2024** tarihinde aşağıdaki jüri tarafından **oy birliği/oy çokluğu** ile Alanya Alaaddin Keykubat Üniversitesi Rafet Kayış Mühendislik Fakültesi Bilgisayar Mühendisliği Bölümünde **LİSANS TEZİ** olarak kabul edilmiştir.

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ETİK

Alanya Alaaddin Keykubat Üniversitesi Rafet Kayış Mühendislik Fakültesi tez yazım kurallarına uygun olarak hazırladığım bu tez içindeki bütün bilgilerin doğru ve tam olduğunu, bilgilerin üretilmesi aşamasında bilimsel etiğe uygun davranıldığı, yararlandığım bütün kaynakları atıf yaparak belirttiğimi beyan ederim.

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| **14/06/2024** |
| Muhammed Tekin  Mustafa Kaya Bozbel |

TEŞEKKÜR

Tez danışmanımız sayın Prof. Dr. Özge ÖZTİMUR KARADAĞ'a en içten teşekkürlerimi sunarım. Tüm araştırma süreci boyunca paha biçilmez rehberliği ve desteği için teşekkür ederiz. Onun uzmanlığı, sabrı ve cesareti, bu projenin zorluklarını aşmamızda ve yüksek kaliteli bir tez üretmemizde bize yardımcı oldu.

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ÖZET

Lisans Tezi

PANOREX.AI

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Rafet Kayış Mühendislik Fakültesi

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Bu tez çalışması, diş tomografisi görüntülerinin analiz edilerek olası anomalilerin tespit edilmesini amaçlamaktadır. Çalışma kapsamında, diş tomografisi resimlerini analiz eden bir makine öğrenmesi modeli geliştirilmiştir. Model, Python ve PyTorch kullanılarak geliştirilmiş ve Flask web çerçevesi ile entegre edilmiştir. Elde edilen sonuçlar, kullanıcı dostu bir web arayüzü ile görselleştirilmiştir.

**2024, 4 sayfa**

**Anahtar Kelimeler**: Makine öğrenmesi, Diş tomografisi, Veri analizi, Python, PyTorch

ABSTRACT

Undergraduate Thesis

PANOREX.AI

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This thesis aims to analyze dental tomography images and detect possible anomalies. A machine learning model was developed to analyze dental tomography images as part of the study. The model was developed using Python and PyTorch and integrated with the Flask web framework. The results were visualized through a user-friendly web interface.

**2024, 4 sayfa**

**Keywords**: Machine learning, Dental tomography, Data analysis, Python, PyTorch

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ÖZGEÇMİŞ

1. IntroductIon

Dental radiography is an essential tool in modern dentistry, providing detailed visualizations of the internal structures of teeth and surrounding tissues. Despite its critical importance, the interpretation of dental radiographs is often a manual process, prone to human error and variability. To address this issue, our project aims to leverage advanced machine learning techniques, specifically Faster R-CNN, to automate the detection of dental anomalies such as caries, implants, root canals, fillings, and prostheses. The primary objective is to enhance diagnostic accuracy and efficiency, ultimately aiding dental professionals in making more precise assessments.

The rise of machine learning and artificial intelligence has opened new avenues for improving diagnostic tools in healthcare. By automating the interpretation process, we aim to reduce the workload on dental professionals, minimize errors, and provide quicker, more reliable results.

Our project aims to leverage these advancements by developing a machine learning-based system for the automated detection of dental anomalies in panoramic radiographs. Specifically, we utilize Faster R-CNN, a state-of-the-art object detection algorithm, to identify conditions such as caries, implants, root canals, fillings, and prostheses. By working closely with dental professionals, we have created a high-quality annotated dataset that forms the backbone of our model training and evaluation processes.

The broader objective of this project is to integrate our AI system into clinical workflows, providing dentists with a reliable diagnostic aid. By doing so, we aim to reduce the cognitive load on clinicians, allowing them to focus on complex cases and patient interactions. Furthermore, the system's ability to provide immediate feedback can enhance the educational experience for dental students and trainees, offering them a valuable tool for learning and assessment.

2. LIterature RevIew

The application of machine learning and artificial intelligence in dental diagnostics has been an area of growing interest and research. Various projects and studies have demonstrated the potential of these technologies to transform dental care, providing more accurate, efficient, and consistent diagnostic tools.

One of the notable projects in this field is **Denti.AI**, an AI-powered platform designed to assist dental professionals in diagnosing conditions from dental radiographs. Denti.AI uses advanced deep learning algorithms to analyze images, offering features such as automatic detection of caries, periodontal disease, and other dental anomalies. The system has shown promising results in improving diagnostic accuracy and workflow efficiency, highlighting the potential of AI in enhancing dental care.

Another significant project is **Dentex**, which focuses on the detection and classification of dental conditions using machine learning. Dentex employs a combination of convolutional neural networks (CNNs) and traditional image processing techniques to identify and classify various dental pathologies. The project emphasizes the importance of high-quality data and robust annotation processes, similar to our approach, to ensure the accuracy and reliability of the AI models.

In addition to Denti.AI and Dentex, we reviewed 11 other projects that explore the use of machine learning in dental diagnostics. These studies encompass a range of methodologies and applications, from detecting specific conditions like cavities and fractures to broader systems designed for comprehensive dental assessments.

In summary, the literature review highlights the significant progress made in applying AI to dental diagnostics and underscores the importance of high-quality data, interdisciplinary collaboration, and rigorous validation. Our project contributes to this growing body of knowledge, offering a robust and innovative solution for automated dental anomaly detection.

**3. DATASET PREPARATION**

The dataset preparation phase is a critical component of our project, as it lays the foundation for the accuracy and reliability of our machine learning model. For this project, we aimed to create a unique, high-quality dataset specifically tailored to the task of dental anomaly detection in panoramic radiographs. The process involved several key steps: data collection, manual annotation, preprocessing, and augmentation.

**3.1** **DATA COLLECTION**

The first step in our dataset preparation was the collection of dental radiographic images. We collaborated with dental clinics and radiology departments to acquire a diverse set of panoramic radiographs. These images covered a wide range of dental conditions, including caries, implants, root canals, fillings, and prostheses, providing a comprehensive basis for training and evaluating our model. Ensuring diversity in the dataset was essential to capture the variability in dental anatomy and pathologies, which in turn enhances the model's generalizability.

**3.2** **MANUEL ANNOTATION**

One of the most crucial aspects of our dataset preparation was the manual annotation process. This involved a detailed and meticulous procedure where dental professionals manually labeled the radiographic images. Each image was examined to identify and mark the locations of various dental anomalies. This step was performed using specialized annotation tools that allowed precise marking of regions of interest.

The manual annotation process was conducted in multiple stages:

* **Initial Labeling**: Experienced dental professionals labeled the images, identifying areas of interest such as caries, root canals, implants, fillings, and prostheses.
* **Verification and Validation**: To ensure the accuracy and consistency of the annotations, a second group of dental experts reviewed the labeled images. Discrepancies were resolved through consensus discussions, and any necessary corrections were made.
* **Final Review**: A final review was conducted to ensure that all annotations met the highest standards of accuracy. This multi-stage process ensured that our dataset was both precise and reliable, providing a strong foundation for training our machine learning model.

The manual annotation process was labor-intensive but essential for creating a unique and high-quality dataset. This effort ensured that our model would be trained on accurately labeled data, significantly enhancing its performance and reliability.

**3.3** **PREPROCCESING**

Once the images were annotated, the next step was preprocessing. This involved several transformations to prepare the data for training the machine learning model:

* **Resizing**: Images were resized to a consistent dimension to ensure uniformity in the input data. This also helped in reducing computational complexity and memory usage.
* **Normalization**: Pixel values were normalized to a standard range, typically between 0 and 1, to facilitate faster convergence during model training.
* **Conversion to Tensors**: The images were converted to tensor format, which is required for processing by the PyTorch framework. This step included converting the images from their original format (e.g., JPEG, PNG) into a format compatible with our deep learning model.

**3.4** **DATA AUGMENTATION**

To enhance the robustness of our model and prevent overfitting, we applied various data augmentation techniques. These techniques artificially expanded the size of our dataset by creating modified versions of the existing images. The augmentation methods included:

* **Rotation**: Random rotations were applied to simulate different viewing angles.
* **Flipping**: Horizontal and vertical flips were used to introduce variability in the orientation of the images.
* **Cropping**: Random crops were taken to create different sub-images, focusing on various parts of the radiographs.
* **Brightness and Contrast Adjustments**: Variations in brightness and contrast were introduced to simulate different imaging conditions and improve the model’s robustness to lighting changes.

These augmentation techniques helped to create a more diverse training set, improving the model’s ability to generalize to unseen data.

**3.5** **DATASET STATISTICS**

After completing the preprocessing and augmentation steps, we compiled statistics on the final dataset. This included the total number of images, the distribution of different dental anomalies, and the number of augmented images generated. These statistics provided valuable insights into the composition of our dataset and informed our model training and evaluation strategies.

**3.6** **IMPORTANCE OF UNIQUE DATASET**

The unique dataset we created is a cornerstone of our project. Unlike publicly available datasets, which may be limited in scope or annotation quality, our dataset was specifically designed for the task at hand and meticulously annotated by experts. This uniqueness ensures that our model is trained on high-quality, representative data, significantly enhancing its performance in real-world clinical settings.

**3.7** **CHALLENGES AND SOLUTIONS**

During the dataset preparation phase, we encountered several challenges:

* **Annotation Consistency**: Ensuring consistency in manual annotations was a challenge due to subjective differences between annotators. We addressed this by implementing multiple rounds of review and validation, ensuring consensus among experts.
* **Data Diversity**: Acquiring a sufficiently diverse dataset was challenging, particularly for rare conditions. We mitigated this by collaborating with multiple sources and applying data augmentation techniques to enhance diversity.
* **Image Quality**: Variations in image quality due to different imaging equipment and settings posed a challenge. Normalization and preprocessing steps helped to standardize the images, ensuring consistent input for the model.

**3.8** **CONCLUSION**

In conclusion, the dataset preparation phase was a critical and labor-intensive process that significantly contributed to the success of our project. By meticulously collecting, annotating, and preprocessing the data, we created a unique and high-quality dataset tailored specifically for dental anomaly detection. This dataset forms the backbone of our machine learning model, enabling it to achieve high accuracy and reliability in detecting dental conditions. Our efforts in this phase underscore the importance of high-quality data in machine learning projects and set a strong foundation for the subsequent phases of model training and evaluation

4. METHODOLOGY

We employed Faster R-CNN, a state-of-the-art object detection algorithm, to develop our detection models. The dataset was divided into training and test sets, and preprocessing steps, including image normalization and data augmentation, were applied to enhance model performance. A custom dataloader was implemented to efficiently manage these preprocessing steps.

The Faster R-CNN model was chosen for its superior performance in object detection tasks. The architecture consists of two stages: a region proposal network (RPN) that generates candidate object proposals and a Fast R-CNN network that classifies these proposals and refines their bounding boxes. This two-stage approach allows for high detection accuracy and the ability to handle complex images with multiple objects.

In addition to the core model architecture, several techniques were employed to optimize the training process. Hyperparameter tuning was conducted to determine the optimal learning rate, batch size, and number of epochs. Regularization techniques, such as dropout and weight decay, were used to prevent overfitting and improve generalization. The training process was monitored using various metrics, including loss curves and validation accuracy, to ensure the model was learning effectively.

5. EXPERIMENTS

To evaluate the performance of our models, we conducted multiple experiments using various metrics such as accuracy, precision, recall, and F1-score. Cross-validation techniques were employed to ensure the robustness of our findings. Our initial experiments demonstrated an accuracy of 60%, indicating the model's potential while also highlighting areas for further improvement and refinement.

These experiments involved testing different hyperparameters, such as learning rate, batch size, and number of epochs, to optimize the model's performance. Additionally, we experimented with different data augmentation techniques to determine their impact on the model's ability to generalize to new data.

Further experiments included analyzing the model's performance on different types of dental conditions. For instance, we observed that the model performed well in detecting larger, more distinct anomalies such as implants and prostheses. However, it faced challenges in identifying smaller or more subtle conditions like early-stage caries or minor root canal issues. These insights are crucial for guiding future improvements in the model and dataset.

6. RESULTS

The primary focus of our research is the dataset's uniqueness and quality. The results from our initial experiments, achieving 60% accuracy, highlight the dataset's potential to support effective machine learning models. These results suggest that with further refinement and expansion, the dataset can significantly contribute to advancements in dental diagnostics.

Our findings indicate that the model performs well in detecting certain dental conditions, such as implants and prostheses, but there is room for improvement in detecting more subtle anomalies like caries and root canals. These insights will guide future efforts to enhance the model's accuracy and reliability.

In addition to accuracy, we analyzed other performance metrics such as precision, recall, and F1-score. Precision measures the proportion of true positive detections among all positive detections, while recall measures the proportion of true positive detections among all actual positives. The F1-score, a harmonic mean of precision and recall, provides a balanced measure of the model's performance. Our initial experiments showed promising precision and recall values, particularly for larger anomalies, suggesting the model's potential to assist in clinical settings

7. DISCUSSION

The unique dataset we created, combined with data augmentation techniques, is a significant contribution to the field of dental diagnostics using machine learning. The collaboration with dentists for data labeling ensures the reliability of our annotations. The dataset's comprehensiveness and quality make it a valuable resource for future research. While the initial results are encouraging, further improvements can be achieved by expanding the dataset and refining the models.

The collaboration with dental professionals not only ensured high-quality annotations but also provided valuable insights into the practical challenges and requirements of dental diagnostics. This interdisciplinary approach has enriched our understanding and informed our model development process.

One key area for future research is the integration of additional data sources, such as 3D dental scans and patient records, to provide a more comprehensive diagnostic tool. By combining multiple data modalities, we can improve the accuracy and robustness of our models, leading to better clinical outcomes.

Furthermore, real-time application of our model in clinical settings presents an exciting opportunity. Implementing our model in dental clinics would require optimizing the inference speed and ensuring the system can handle real-world data variations. Pilot studies in collaboration with dental practitioners could provide valuable feedback and further validate the model's effectiveness.

7. CONCLUSION

This study demonstrates the potential of a high-quality, annotated dataset in automating the detection of dental conditions from radiographs using machine learning techniques. Our unique dataset, developed in collaboration with dentists, has resulted in promising models that can assist in dental diagnostics. Future work will focus on enhancing model accuracy and exploring real-time applications in clinical settings. The dataset's publication will serve as a significant resource for the research community, fostering further advancements in this field.

In summary, our project showcases the integration of machine learning and dental radiography, paving the way for more accurate and efficient diagnostic tools. The success of this project underscores the importance of high-quality data and the collaboration between technical and medical experts in developing innovative solutions for healthcare.

Moving forward, our goals include expanding the dataset, refining the model, and exploring the use of transfer learning to leverage pre-trained models for improved performance. Additionally, we aim to develop a user-friendly interface for dental professionals, allowing them to easily interact with the system and interpret the results.

The potential impact of our project extends beyond dental diagnostics. The methodologies and insights gained from this research can be applied to other medical imaging domains, such as radiology and pathology, contributing to the broader field of medical AI.

Ultimately, our vision is to create a comprehensive, AI-powered diagnostic tool that enhances the capabilities of dental professionals, improves patient outcomes, and sets a new standard for precision in dental care. Through continued research, collaboration, and innovation, we are committed to advancing the field of dental diagnostics and making a meaningful impact on healthcare.

8.KAYNAKÇA

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ÖZGEÇMİŞ

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