PanoraTooth

Mohammad Sufiyaan Khan
B. Tech
School of Engineering
Computer Science – AI&ML
Malla Reddy University, India.

M. Vaishnav
B. Tech
School of Engineering
Computer Science – AI&ML
Malla Reddy University, India.

R. Vaishnavi
B. Tech
School of Engineering
Computer Science – AI&ML
Malla Reddy University, India.

B. Vaishnavi
B. Tech
School of Engineering
Computer Science – AI&ML
Malla Reddy University, India.

P. Vaishnavi
B. Tech
School of Engineering
Computer Science – AI&ML
Malla Reddy University, India.

G. Vaishnavi
B. Tech
School of Engineering
Computer Science – AI&ML
Malla Reddy University, India.

Guide: Siva Kumar
Asst Professor
School of Engineering
Computer Science – AI&ML
Malla Reddy University, India.

1.Abstract: *In dentistry, radiological examinations help specialists by showing structure of the tooth bones with the goal of screening embedded teeth, bone abnormalities, cysts, tumours, infections, fractures, problems in the temporomandibular regions, just to cite a few. Sometimes, relying solely in the specialist's opinion can bring differences in the diagnoses, which can ultimately hinder the treatment. Tooth segmentation using panoramic X-rays presents a pivotal advancement in the realm of dental image analysis. Panoramic X-rays, offering a comprehensive view of the entire dentition, have become integral in dental diagnostics and treatment planning. We propose a segmentation system based on mask region-based convolutional neural network to accomplish an instance segmentation.*

Keywords: Python, Machine Learning (DenseNet201), TPU

2. INTRODUCTION

Manual segmentation is a meticulous and time-consuming process, requiring expertise in dental anatomy and familiarity with the imaging software, and it is often limited by high inter-operator variability. Introducing an automated assistance system could mitigate interrater variability and facilitate more reliable and precise evaluations of panoramic radiographs, particularly for less experienced professionals while saving time and improving efficiency.

The segmentation of teeth regions in panoramic dental X-ray images through machine learning involves employing algorithms to automatically identify and delineate the boundaries of teeth. By leveraging image processing and machine learning techniques, the system learns to differentiate between teeth and background structures. This automated segmentation enhances diagnostic processes, aids in treatment planning, and accelerates dental image analysis. The goal is to develop a model capable of accurately and efficiently isolating the tooth structures from panoramic X-rays, contributing to improved clinical assessments and facilitating dental healthcare practitioners in their diagnostic tasks.

Leveraging advanced techniques like machine learning, particularly on panoramic X-rays, enhances the precision of this process. By integrating neural networks and analysing dental images, our approach aims to provide accurate and efficient segmentation, facilitating a more comprehensive understanding of dental structures for improved patient care.

3. LITERATURE REVIEW

The literature in this area often covers various methods and techniques employed for accurate segmentation in dental imaging. This paper discusses the application of image processing techniques, such as thresholding, edge detection, and morphological operations, to enhance the quality of panoramic X-ray images for better segmentation accuracy. Architectures like Mask R-CNN have been adapted and customized for dental image segmentation tasks.

The study provides insights into effectiveness of DenseNet201 Model in segmentation of tooth for a large-scale medical industry. Transfer learning, where pre-trained models are fine-tuned on dental X-ray datasets, has been utilized to address the challenge of limited annotated data. The study evaluates the algorithm's performance using real-world data and discusses the results, demonstrating the potential of DenseNet201 model in segmenting tooth boundary problems. The system's adaptability may be limited in cases where there are frequent changes in scheduling requirements that were not initially considered during the algorithm design.

3.1 Existing System:

We proposed a Dense net201 trained on image collected from one public database (ARTURO-BANDINI -JR), divided into for 8030,780,473 the training, validation, and test sets, respectively. Our model achieved high detection accuracy on the test set (76.8%) with a Dice index (0.72). Through deepening the performance of individual teeth, it can be noted that some classes do not achieve 100% accuracy. It is more common in this situation that the few teeth that are present are misclassified, the lower performance is, therefore, for the majority, due to these particular and more challenging cases.

3.2 Limitations:

1. Limited Training Data: Insufficient or biased training data may impact the model's ability to generalize across diverse cases.

2. Image Quality Issues: Poor-quality images or distortions in the dental images may hinder the model's performance.

3. Interference from Adjacent Structures: Structures surrounding the teeth, such as bones or soft tissues, may interfere with accurate segmentation, posing challenges in distinguishing between teeth and adjacent components.

4. Limited Interpretability: Deep learning models, especially complex ones, may lack interpretability, making it challenging to understand and explain the decision-making process.

5. Continuous Monitoring and Updates: The model's performance might degrade over time due to changes in data distribution or evolving clinical practices. Continuous monitoring and regular updates may be necessary to maintain efficacy.

3.3 Proposed System:

Our project develops a machine learning model capable of automatically segmenting the teeth regions in panoramic X-rays and dental images. This involves precise delineation of individual teeth to provide a detailed and accurate representation.

Increase the efficiency of dental image analysis by reducing the manual effort required for teeth segmentation.

Improve the diagnostic capabilities of dental imaging through automated segmentation. Accurate teeth segmentation can assist dental professionals in the detection of abnormalities, diseases, and other oral health conditions.

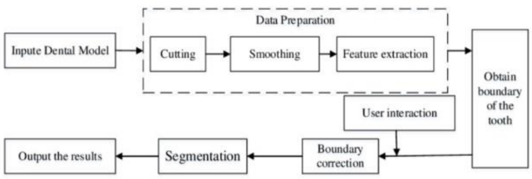

Figure 1: Working of DenseNet201 Model

4. PEOBLEM STATEMENT

Within the scope of my project, the focus is on revolutionizing the process of timetable generation in educational settings using machine learning. The challenge at hand revolves around creating an intelligent and flexible system capable of efficiently scheduling courses, instructors, and resources within educational institutions. Conventional methods frequently fall short when confronted with the complexities of diverse constraints and preferences, resulting in less-than-optimal scheduling outcomes.

In this project, the primary objective is to employ machine learning, specifically leveraging genetic algorithms, to significantly improve the efficiency and effectiveness of the timetable generation process. By integrating genetic algorithms into the system, we aim to address the limitations of traditional approaches and introduce adaptability that can handle the intricate requirements of educational scheduling. The overarching goal is to enhance the quality of generated timetables, ensuring they align more closely with the unique needs and constraints of educational institutions.

4.1 Description of Data:

The success of any tooth segmentation project relies heavily on the availability of a high-quality and diverse dataset. In this context, we present the "Dental Panoramic X-ray Dataset for Tooth Segmentation," a comprehensive collection designed to facilitate the development and evaluation of automated tooth segmentation algorithms.

Dataset Source:

The dataset comprises panoramic X-ray images obtained from diverse dental clinics and institutions, ensuring a broad representation of patients across different demographics. The images were captured using standard dental radiography equipment, providing a realistic and varied set of challenges for accurate tooth segmentation.

Characteristics of the Dataset:

1. Image Resolution: The dataset includes high-resolution panoramic X-ray images with varying levels of detail, simulating real-world clinical scenarios.

2. Diversity: Images showcase a diverse range of oral conditions, encompassing cases with varying tooth shapes, sizes, and positions. Additionally, the dataset accounts for instances of overlapping teeth, dental anomalies, and varying image qualities.

3. Annotation: Each image in the dataset is meticulously annotated by dental professionals to provide ground truth segmentation masks for individual teeth. These annotations serve as the reference standard for evaluating segmentation accuracy.

5. METHODOLOGY

This research investigates the application of machine learning for automatic segmentation of teeth regions in dental x-rays and panoramic images. The focus lies on developing a robust and efficient model capable of accurately delineating individual teeth boundaries, contributing to improved dental image analysis and diagnosis.

5.1 Data Preparation:

1. **Data Acquisition:**
○ Panoramic X-rays and dental images were collected from various sources, ensuring
diversity and quality.
○ Images were standardized to a consistent format and resolution.
○ Preprocessing techniques were applied to address noise, artifacts, and
inconsistencies.

2. **Data Labeling:**
○ Dental experts manually annotated tooth regions in the images using specialized
tools.
○ Consistency across annotators was ensured through standardized protocols and
quality control measures.
○ Data augmentation techniques were employed to increase the dataset size and
enhance model generalizability.

5.2 Model Architecture:

1. **Model Selection**:
○ DenseNet201 was chosen as the pre-trained model for feature extraction due to its
efficient architecture and strong performance on image classification tasks.
○ A custom classifier head was designed on top of the pre-trained model, consisting of
dense layers with appropriate activation functions and dropout regularization.
○ Adam optimizer was employed for updating model weights, and sparse categorical
cross-entropy served as the loss function for multi-class segmentation.

2. **Training and Optimization**:

1. Training Process:
○ The model was trained on the preprocessed and augmented data using a mini-batch
gradient descent approach.
○ Early stopping and Reduce LR On Plateau callbacks were implemented to prevent
overfitting and optimize learning rate during training.
○ Model hyperparameters were tuned using grid search or other optimization
techniques to achieve optimal performance.

2. Evaluation and Validation:
○ Model performance was evaluated on a separate validation dataset using metrics such as accuracy, precision, recall, F1 score, and dice coefficient.
○ Confusion matrix and classification report were generated to analyze per-class performance and identify potential biases or weaknesses.
○ Qualitative evaluations were conducted by visually inspecting predicted segmentation masks and comparing them to ground truth annotations.

3. **Model Improvement and Deployment**:

1. Post-processing:
○ Morphological operations like dilation and erosion were applied to refine segmented regions and remove small artifacts.
○ Techniques like active learning or semi-automatic segmentation could be explored to further improve data efficiency and annotation accuracy.

2. Deployment and Integration:
○ The model was optimized for efficient inference and deployed in a user-friendly interface for dental professionals.
○ Integration with existing dental imaging software could be developed to streamline the workflow and facilitate seamless adoption.

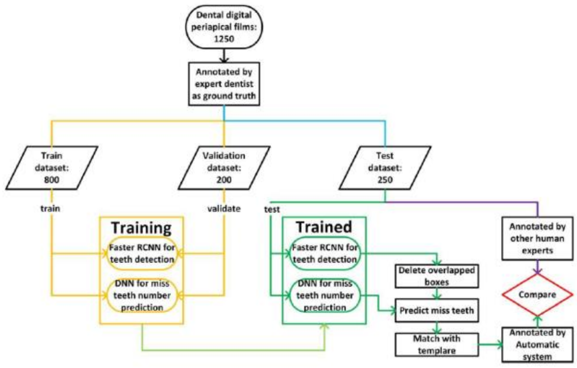

Figure 2: Model Architecture

5.3 Pre-processing Steps:

In the context of panoramic X-ray image analysis for PanoraTooth project, various algorithms may be employed for specific tasks. Here are the algorithms we used:

1. Contrast Limited AHE (CLAHE): Contrast Limited Adaptive Histogram Equalization (CLAHE) is an image processing technique used to enhance the contrast of an image. It is an extension of the traditional Adaptive Histogram Equalization (AHE) method. The primary purpose of CLAHE is to overcome some of the limitations of AHE, particularly in the case of images with varying illumination.

2. Adaptive Histogram Equalization: Adaptive histogram equalization (AHE) is a computer image processing technique used to improve contrast in images. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image.

5.4 Data Augmentation:

The data augmentation techniques used in this code are:

1. **Image resizing**: All images are resized to a standard size of 256x256 pixels. This ensures that all images are processed by the model in a consistent way.

2. **Image flipping**: Images are randomly flipped horizontally (left-right) with a 50% chance. This helps the model learn to recognize objects regardless of their orientation.

3. **Image color normalization**: Images are normalized by dividing them by 255. This ensures that all pixels have values between 0 and 1, which makes them easier for the model to process.

4. **CLAHE operation**: This operation is used to improve the contrast of the images. This makes it easier for the model to distinguish between different features in the images.

These data augmentation techniques help to artificially increase the size of the training dataset, which can lead to improved model performance. They can also help to improve the model's generalizability, which means that it is more likely to perform well on unseen data.

6. EXPERIMENTAL RESULTS

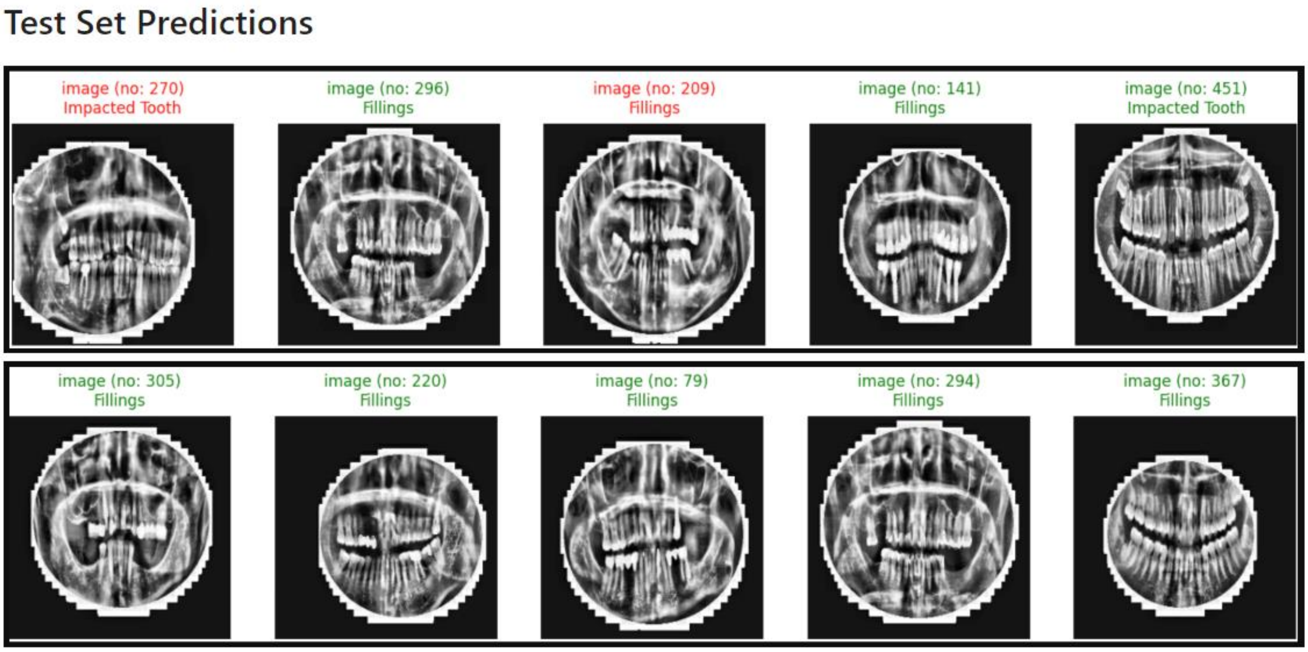

Figure 3: Test Set Predictions

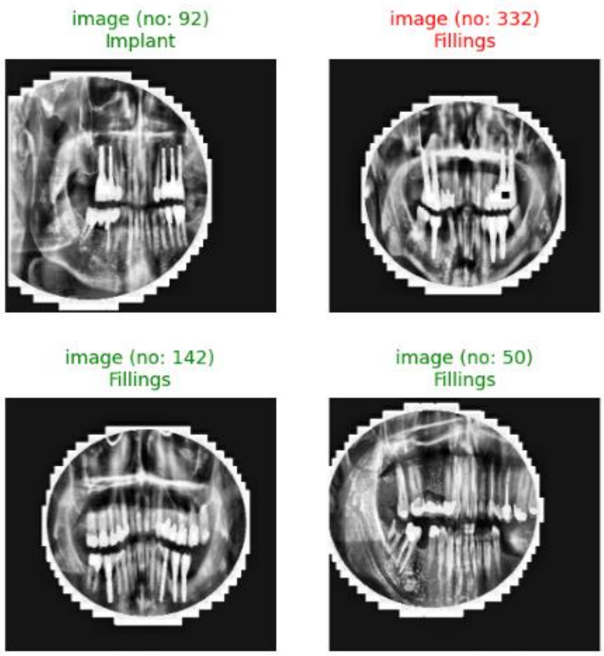

Figure 4: Random Predictions

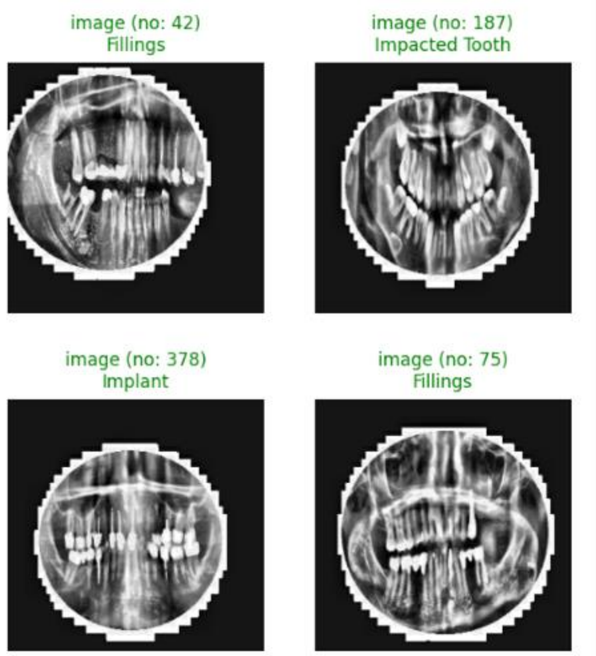

Figure 4: Random Predictions

	precision	recall	f1-score	support
Fillings	0.77	0.92	0.84	315
Implant	0.70	0.30	0.42	104
Impacted Tooth	0.68	0.88	0.77	32
Cavity	0.33	0.23	0.27	22
accuracy			0.75	473
macro avg	0.62	0.58	0.57	473
weighted avg	0.73	0.75	0.72	473

Figure 5: Classification Report

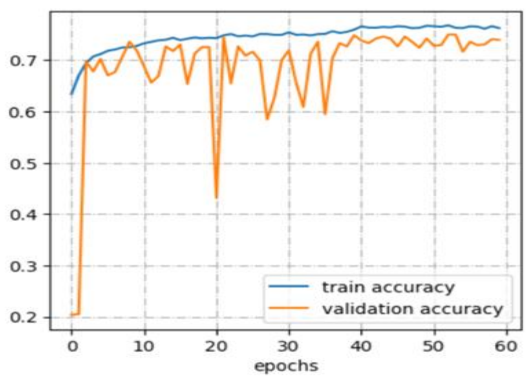

Figure 6: Accuracy Graph

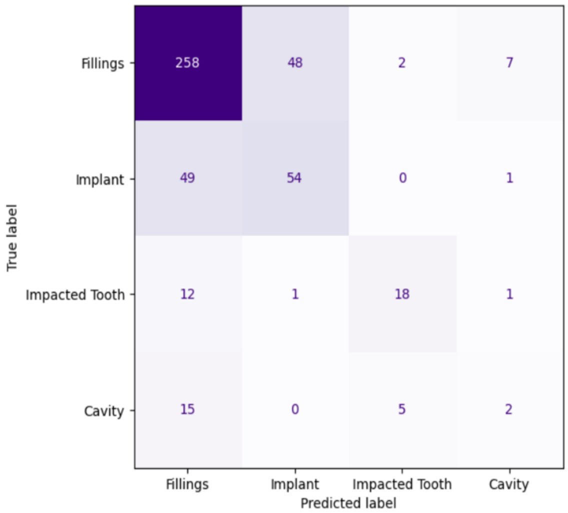

Figure 7: Confusion Matrix

The Test Accuracy of the model is 76.8%.

6.1 Model Evaluation Metrics:

- After the model is generated, it is accessed through a set of metrics.
- Accuracy: The accuracy is defined as the percentage of correctly classified teeth; a tooth is considered correctly classified if the Intersection over Union (IoU) of the original annotation (ground truth) with a predicted object of the same class is above a threshold. Measures the overall correctness of the DenseNet-201 model predictions by comparing the predicted labels and the true labels in the test set.
- Classification report: Provides a detailed breakdown of precision, recall, and F1-score for each age group, offering insights into the model's performance on individual classes.
- Confusion Matrix: Visualizes the number of fillings, implants, impacted tooth, cavity
- Test Set Prediction: In this a function which creates a random test set and predictions in which Red title = false prediction and Green title = true prediction.

6.2 Comparison to existing methods:

1. *Complex Pattern Recognition with Dense Layers*: The dense layers with dropout regularization in DenseNet201 contribute to capturing complex patterns in the data, which is essential for understanding the intricate constraints and preferences associated with timetable generation. This can lead to more accurate and adaptable scheduling outcomes.

2. Multi Class Classification Support: DenseNet201 Model is capable of handling multi-class classification tasks, making it suitable for scenarios where scheduling involves the classification of different classes (e.g., courses, instructors, resources). This aligns well with the multi-faceted nature of timetable generation.

3. *Transfer Learning*: DenseNet201 is pre-trained on large-scale image datasets, providing a head start in learning generic features. Leveraging transfer learning, you can apply the knowledge gained from image-related tasks to your timetable generation project. This can lead to faster convergence during training and potentially better generalization to your specific scheduling problem.

7. CONCLUSION

In conclusion, panoramic X-rays serve as valuable tools for teeth segmentation, offering a comprehensive view of the oral structures. The segmentation process aids in precise analysis, diagnosis, and treatment planning. This method enhances dental care by providing detailed insights into tooth morphology, facilitating effective interventions and improving overall patient outcomes. Furthermore, the accuracy and efficiency of teeth segmentation using panoramic X-rays contribute to advancements in digital dentistry. The detailed three-dimensional representation allows for a thorough assessment of dental conditions, assisting clinicians in identifying issues such as abnormalities, caries, or misalignments. As technology continues to evolve, the integration of panoramic X-ray segmentation holds promise for even more refined and personalized dental care approaches.

8. FUTURE SCOPE

1. *Enhanced Adaptability*: Continuous refinement and optimization of the DenseNet201 model can lead to improved adaptability to diverse and evolving scheduling requirements.

2. *Integration of Real-Time Data*: Consider incorporating real-time data into the scheduling process. This could involve dynamically updating schedules based on changing circumstances, such as unexpected events, resource availability, or modifications to course offerings.

3. *Integration with Learning Management Systems (LMS)*: Collaborate with existing educational technology platforms by integrating your scheduling system with popular Learning Management Systems.

9. REFERENCES

[1] Keras, DenseNet201 Model, Model Available: https://keras.io/api/applications/densenet/

[2] Arturo Bandini Jr, Machine Learning Engineer, DenseNet201 Model Available: https://www.kaggle.com/code/banddaniel/dental-x-rays-classification-test-f1-score-0-72

[3] Afnan Ghafoor, Seong-Yong Moon and Bumshik Lee, 2023, Multiclass Segmentation Using Teeth Attention Modules for Dental X-Ray Images, Electronic ISSN: 2169-3536.

[4] Karen Panetta, Rahul Rajendra, Aruna Ramesh, Shishir Paramathma Rao and Sos Agaian, 2021, Tufts Dental Database: A Multimodal Panoramic X-Ray Dataset for Benchmarking Diagnostic Systems, PubMed ID: 34606466.