DEVELOPMENT OF AN AUTOMATED DENTAL RADIOGRAPHY ANALYSIS SYSTEM USING YOLO FOR THE DETECTION OF DENTAL DISEASES

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ABSTRACT

This project is a system designed to revolutionize dental disease diagnostics by focusing on the detection of dental fillings, impacted teeth, and implants using artificial intelligence. Traditional diagnostic approaches are time-consuming, require highly professional qualifications, and rely on manual analysis. To address these challenges, this project proposes an efficient and accurate diagnostic tool for dentists and dental students. The solution supports a user-friendly webpage that uses the YOLOv5 (You Only Look Once Version 5) model for rapid and precise analysis of dental radiography images. The methodology includes training the YOLOv5 model using a dental radiography dataset and integrating the analysis algorithm into a web interface. The result is a website with an overall high accuracy of 0.97 that automatically diagnoses dental disease based on radiographs, serving as both a medical diagnostic tool and an educational resource for dental practice and education.

Keywords: object detection, YOLOv5, deep learning, dental radiography images

1. INTRODUCTION

According to the World Health Organization (WHO), nearly 3.5 billion people worldwide suffer from dental diseases, the common diseases among them are noncommunicable diseases such as cavities and implants (WHO highlights oral health neglect affecting nearly half of the world's population, 2022). Despite the high prevalence of dental health issues, most patients choose not to go to the hospital and dental clinics for medical treatment, indicating a need for more accessible and efficient diagnostics and care (Saub, 2013).

In the field of dentistry, diseases diagnostics rely on traditional approaches which are manually identified by dentists. This approach is time-consuming and needs highly qualified professionals that caused imprecision and inaccuracy. Dentistry has extraordinarily special situations and development unlike other branches of medicine who are attached to General Hospitals. Dentistry is one of the oldest medical professionals and the development achieved remarkable results. Nowadays, People are used to going to dental clinics instead of general hospitals for treatment. Individual clinics unable to equip with advanced medical equipment in time and that caused the dental service unaffordable and time-consuming.

Dental radiographs, commonly known as X-rays, are radiographs used to diagnose hidden dental structures, malignant or benign masses, bone loss, and cavities. Dental radiographs are a useful and necessary tool in the diagnosis and treatment of dental diseases (The use of dental radiographs: Update and recommendations, 2006).

The You Only Look Once Version5 (YOLOv5) algorithm is a popular deep learning-based object detection model known for its speed and accuracy (Joseph Redmon, 2016). It has been adapted for various applications, including the detection of features in radiography images.

YOLOv5 has demonstrated high accuracy in detecting tumors in radiography images. Studies have shown YOLOv5 achieving over 90% precision in identifying lung nodules in chest X-rays, significantly helping in the early diagnosis of lung cancer (Haytham Al Ewaidat, 2022). YOLOv5-based systems have been successfully integrated into clinical workflows, providing preliminary diagnostic results that assist radiologists (Pincay Silva, 2019). This integration has led to improved diagnostic efficiency and reduced the workload for radiologists.

Due to the difficulty in collecting datasets for dental diseases, the application currently focuses on three specific dental conditions: fillings, impacted teeth, and implants. The application serves as medical equipment for dentists to reduce diagnostic time and practical teaching tool for dental students to learn and comprehend knowledge.

2. OBJECTIVE

This project aims to develop and test automated dental radiography analysis system using artificial intelligence, revolutionizing traditional dental diagnosis and providing quick and precise dental disease identification.

1. Develop an AI-driven system, the DentistFree System, for automated detection and diagnosis of dental diseases using radiographic images.

2. Utilize the YOLOv5 model and advanced data augmentation techniques to achieve rapid and accurate identification of three dental diseases: fillings, impacted teeth, and implants.

3. Create a user-friendly web interface that supports both clinical use by dentists and educational purposes for dental students.
4. Validate the system's performance through training, validation, and comparison with traditional diagnostic methods.

3. METHODOLOGY

3.1. Dataset

The dental radiography dataset includes four categories of dental conditions: cavities, fillings, impacted teeth, and implants. This dataset is systematically divided into three subsets: the Training Set, Test Set, and Validation Set, consisting of a total of 1,272 dental radiographic images, each accompanied by an annotation file for disease detection purposes (MOMENI, 2024).

Figure 1. Dental Radiography Dataset. (MOMENI, 2024)

The training set consists of 1,076 dental radiographic images used to train the YOLOv5 model. The test set has 74 images to evaluate the model's performance and generalization. The validation set includes 122 images to help optimize the model's hyperparameters.

3.2. Data preprocessing

1. Initial Dataset Composition and Cleaning

After reviewing the dataset, three images without annotations were removed, reducing the total to 1,269 images. The updated distribution is: 1,075 images for training, 121 for validation, and 73 for testing. This adjustment did not significantly affect the original proportions.

2. Dataset Rebalancing

To achieve a more balanced dataset distribution, the initial split was reconfigured into an 8:1:1 ratio. The new distribution resulted in 1,009 images for the training set (80%), 129 images for the validation set (10%), and 131 images for the test set (10%).

3. Image Resizing

The dataset images, initially sized at 512x256 pixels, were resized to 640x320 pixels, maintaining the same aspect ratio. This resizing was necessary to fit YOLOv5's preferred input size of 640x640 pixels, with additional pixels automatically filled by the YOLOv5 model.

4. Dataset Annotation and Class Distribution

A comprehensive health check of the dataset revealed a total of 9,283 annotations: 6,096 for fillings, 2,047 for implants, 641 for cavities, and 498 for impacted teeth, averaging 7.3 annotations per image. The dataset displayed an imbalance, with the 'Fillings' class having most annotations, while 'Cavities' and 'Impacted Teeth' were underrepresented.

Table 1. Dataset Health Check Condition

Class	**Annotations**	**Health Check**
Fillings	6097	Overrepresented
Implant	2047	Well Represented
Cavity	641	Underrepresented
Impacted Tooth	498	Underrepresented
Total	9283	N/A

5. Consideration of Cavities

Cavities, especially in early stages, might not be effectively detected through X-rays due to their subtle appearance and imaging limitations. The dataset was modified to exclude cavities if the YOLOv5 model did not achieve 85% accuracy.

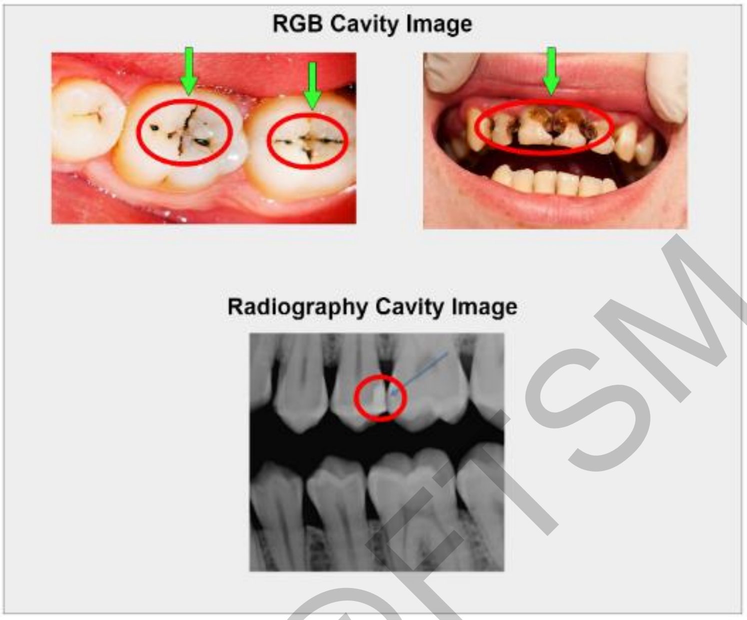


Figure 2. Cavity image contrast in RGB and Radiography. (What is a Cavity, 2022)

6. Data Augmentation in YOLOv5

YOLOv5 employs data augmentation to enhance model performance by artificially increasing the training data diversity. Three levels of augmentation were utilized: no-augmentation, low-augmentation, and high-augmentation, each with specific hyperparameters:

hyp.no-augmentation.yaml: Trains the YOLOv5 model without any data augmentation.

hyp.scratch-low.yaml: Applies a low level of data augmentation.

hyp.scratch-high.yaml: Applies a high level of data augmentation.

7. Experimental Preprocessing and Augmentation

To explore various preprocessing and augmentation techniques, five versions of the dataset were prepared:

Original Dataset: No augmentation before training.

Static Crop Dataset: a fixed-size rectangular region is extracted from an image.

Rotation at Bounding Box Level Dataset: Images rotated by 45 degrees, with three outputs per training example.

Rotation at Image Level Dataset: Images rotated by 45 degrees, with three outputs per training example.

Cutout and Mosaic Dataset: Augmented using Cutout and Mosaic techniques.

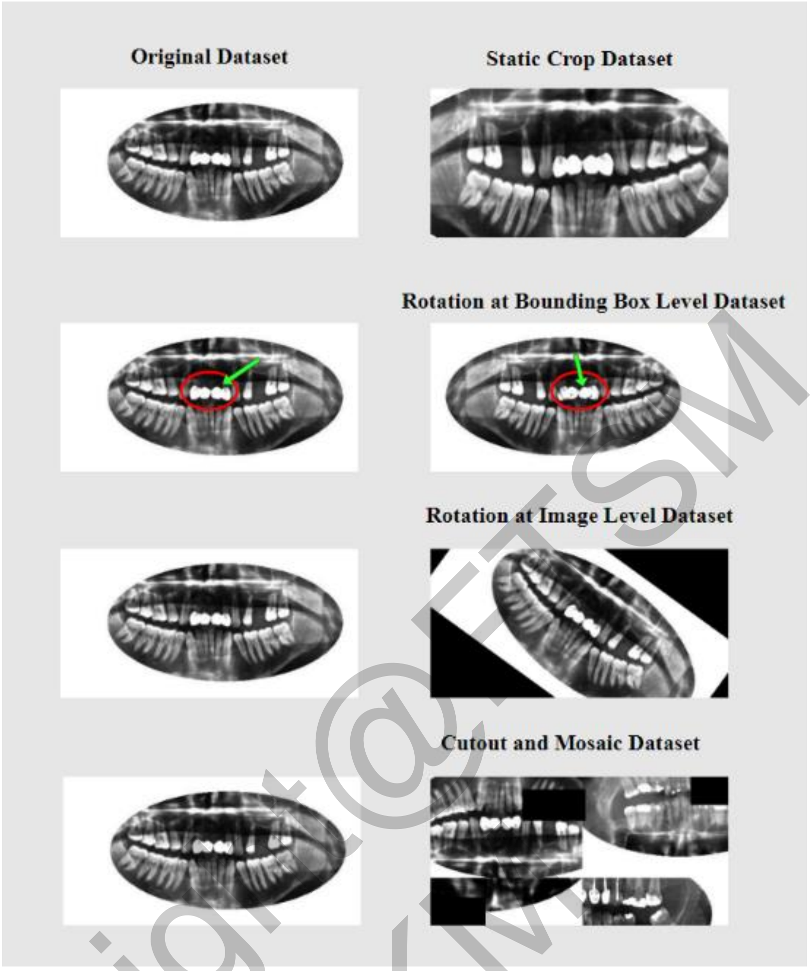


Figure 3. Four Versions Datasets.

Each dataset version underwent conversion to the YOLOv5 PyTorch format.

3.3. Model Training

After completing data preprocessing, the YOLOv5 model was trained using both the original and modified datasets to evaluate performance across different augmentation configurations. The training aimed to determine whether to retain the cavity class based on detection performance and to optimize the model for detecting fillings, impacted teeth, and implants.

1. Initial Dataset Composition and Cleaning

The YOLOv5 model was trained on the original dataset with three levels of automatic augmentation: no augmentation, low augmentation, and high augmentation, each for 100 epochs. The results showed that the cavity class consistently had the lowest accuracy, with a peak of 0.65 under high augmentation, highlighting the challenge of detecting cavities in X-ray images, especially in early stages or on biting surfaces. In contrast, the fillings class showed high accuracy across all configurations, with a maximum of 0.89 in both low and high augmentation scenarios. Impacted teeth detection improved significantly with increased augmentation, reaching 0.80 accuracy with high augmentation. The implant class consistently performed well, achieving 0.93 accuracy with high augmentation. Overall, precision and recall improved with higher augmentation levels, with the highest precision (0.821) and recall (0.744) observed with low and high augmentation, respectively. The mean Average Precision (mAP@0.5) peaked at 0.76156 with high augmentation. Due to the low performance in detecting cavities, the decision was made to exclude the cavity class if accuracy did not reach 85%, focusing instead on fillings, impacted teeth, and implants.

Table 2. Original Dataset Model Training results

Augmentation	Cavity Accuracy	Fillings Accuracy	Impacted Tooth Accuracy	Implant Accuracy	Overall Precision	Overall Recall	mAP@0.5	mAP@0.5:0.95
No	0.10	0.81	0.40	0.88	0.63371	0.54822	0.56417	0.33082
Low	0.49	0.88	0.67	0.92	0.82192	0.69712	0.75095	0.47712
High	0.65	0.89	0.80	0.93	0.75314	0.74414	0.76156	0.49067

2. Training with the Modified Dataset

The modified dataset, excluding the cavity class, was used to further train the YOLOv5 model with no augmentation, low augmentation, and high augmentation. Results showed significant improvements, especially with high augmentation. Models without augmentation performed worse. Low augmentation provided notable improvements, particularly for the original dataset, while high augmentation further enhanced performance, especially in mAP scores.

The original dataset consistently performed well, with the highest mAP@0.5 score of 0.8877 and an overall accuracy of 0.97 for implants under high augmentation. The static crop dataset performed slightly lower, indicating the importance of retaining the full image context. Rotation at the bounding box and image levels provided moderate improvements, with the highest impacted tooth accuracy of 0.72 observed under high augmentation at the image level.

The fillings class maintained the highest accuracy across all experiments, reaching up to 0.93 with high augmentation at the bounding box level. The impacted teeth class showed significant improvement with augmentation, achieving an accuracy of 0.79 and 0.75 in the original and static crop datasets respectively with high augmentation. The implant class consistently achieved high accuracy, peaking at 0.97 with high augmentation in both the original and image level datasets.

Overall, the highest precision (0.9022) and recall (0.8104) were observed with low and high augmentation in the original dataset. The mean Average Precision (mAP@0.5) peaked at 0.8877 with high augmentation in the original dataset, and mAP@0.5:0.95 reached 0.5897 with high augmentation.

Table 3. Modified Dataset Model Training results

Dataset	Augmentation	Fillings Accuracy	Impacted Tooth Accuracy	Implant Accuracy	Overall Precision	Overall Recall	mAP@0.5	mAP@0.5:0.95
Original	No	0.86	0.47	0.87	0.7422	0.6858	0.7404	0.4473
Original	Low	0.92	0.74	0.94	0.9022	0.8079	0.8627	0.5781
Original	High	0.91	0.79	0.97	0.8962	0.8104	0.8877	0.5897
Static Crop	No	0.79	0.57	0.93	0.7982	0.7235	0.7638	0.4895
Static Crop	Low	0.82	0.75	0.95	0.9159	0.7792	0.8445	0.5821
Static Crop	High	0.88	0.75	0.96	0.8659	0.8104	0.8694	0.5884
Bounding box	No	0.83	0.57	0.88	0.8112	0.7217	0.7403	0.4566
Bounding box	Low	0.89	0.62	0.93	0.8497	0.7913	0.8310	0.5513
Bounding box	High	0.93	0.70	0.95	0.8370	0.8177	0.8521	0.5578
Image level	No	0.84	0.70	0.93	0.8479	0.7737	0.7977	0.4925
Image level	Low	0.91	0.70	0.95	0.8878	0.8155	0.8602	0.5656
Image level	High	0.88	0.72	0.97	0.8822	0.8173	0.8884	0.5651

(Note: The dataset now only has 3 classes: fillings, impacted teeth, and implants. Original dataset has 1269 images, remaining datasets has 3287 images.)

3. Advanced Augmentation Techniques

To improve the model's performance, particularly for identifying impacted teeth, advanced data augmentation techniques like Cutout and Mosaic were applied. Cutout involves masking random sections of an image to make the model better at handling occlusions, while Mosaic merges four training images into one, providing varied contexts and enhancing overall robustness.

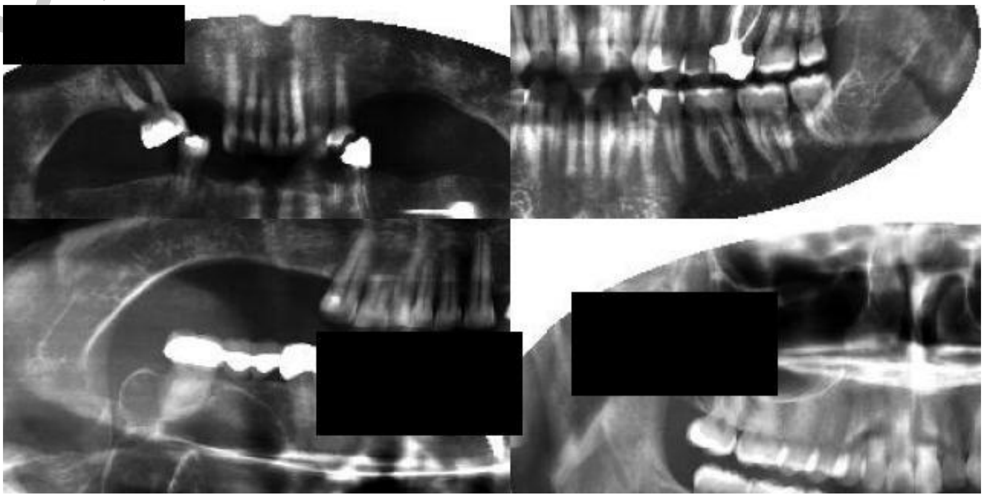


Figure 4. Dataset after Cutout and Mosaic.

Training with these techniques and different levels of augmentation significantly improved the model's performance, with the impacted teeth class reaching 1.00 accuracy with low augmentation and maintaining high performance with high augmentation.

Table 4. Cutout and Mosaic Experiment Results

Dataset	**Augmentation**	**Images**	**Fillings Accuracy**	**Impacted Tooth Accuracy**	**Implant Accuracy**	**Overall Precision**	**Overall Recall**	**mAP@0.5**	**mAP@0.5:0.95**
Cutout and Mosaic Dataset	No	3287	0.92	0.67	0.95	0.92367	0.82393	0.88542	0.60354
	Low		0.97	1.00	0.98	0.97475	0.97726	0.98472	0.72978
	High		0.97	0.97	0.95	0.97338	0.97481	0.98373	0.70924

4. Comparison with Faster-RCNN

After achieving more than 85% accuracy using the Cutout and Mosaic dataset with minimal augmentation, we compared the model's performance with a Faster-RCNN model as a benchmark. The results showed that YOLOv5 performed significantly better than Faster-RCNN in terms of accuracy, precision, recall, and mAP metrics. This strongly suggests that YOLOv5 is the better choice for dental X-ray detection tasks due to its superior performance.

Table 5. Performance Contrast between Faster-RCNN and YOLOv5

Model	**Epochs**	**Fillings Accuracy**	**Impacted Tooth Accuracy**	**Implant Accuracy**	**Overall Precision**	**Overall Recall**	**mAP@0.5**	**mAP@0.5:0.95**
Faster-RCNN	100	0.20	0.17	0.33	0.38	0.32	0.37	0.23
YOLOv5	100	0.97	1.00	0.98	0.97475	0.97726	0.98472	0.72978

5. Model Validation

After comparing YOLOv5 with Faster-RCNN, it was clear that YOLOv5 outperformed Faster-RCNN. The YOLOv5 model, trained with the Cutout and Mosaic Dataset with minimal augmentation, was chosen for deployment.

Validation was crucial to ensure the model's effectiveness on new data. During validation, precision was 0.972, slightly lower than the training phase's 0.974, indicating high accuracy and few false positives. Recall in validation was 0.953, compared to 0.977 in training, showing effective identification of true positives with a slight decrease. Mean Average Precision at 0.5 IoU for validation was 0.976, close to the training phase's

0.984, indicating consistent performance. Mean Average Precision across IoU thresholds (0.5 to 0.95) for validation was 0.724, compared to 0.729 in training, demonstrating robustness across different overlap levels. Precision, recall, and harmonic mean curves showed consistent performance in both training and validation, confirming the model's reliability.

Table 6. Evaluation Metrics for Model Training and Validation Phases

Phases	**Precision**	**Recall**	**mAP@0.5**	**mAP@0.5:0.95**	**F1_curve**	**P_curve**	**PR_curve**	**R_curve**
Training	0.974	0.977	0.984	0.729	0.95	0.96	0.99	0.97
Validation	0.972	0.953	0.976	0.724	0.96	0.94	0.97	0.96

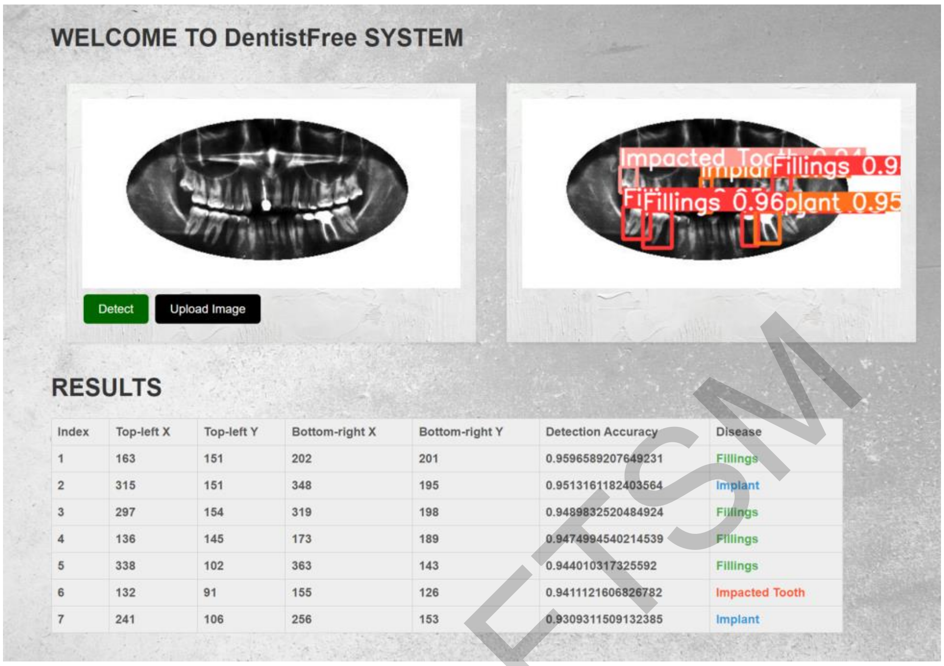
The validation results confirmed that the YOLOv5 model, trained with the Cutout and Mosaic Dataset with Low augmentation, generalizes well to new, unseen data. The evaluation metrics for the validation phase closely aligned with those of the training phase, indicating that the model had not overfitted and maintained high performance on new data.

6. Web Interface Integration

The development of the webpage for this project combined both frontend and backend components to create a user-friendly and functional application. This included setting up a Flask application, configuring routes for various functions, ensuring secure file storage and backups, integrating a database to store image paths, and using templates to render dynamic content.

The backend of the web application was built using Flask, a lightweight web framework in Python ideal for creating simple yet powerful web apps. Key steps in the development included configuring the app.py file, setting up routes for image uploads and result displays, and implementing secure file storage to ensure the integrity and availability of uploaded images.

The DentistFree System’s web interface is designed to be intuitive and informative, offering a smooth experience for users to detect and understand dental diseases. The home page allows users to upload images and start the detection process. After an image is uploaded, the result page shows detection results with coordinates and accuracy metrics, along with links to detailed disease information. Each disease has a dedicated page with comprehensive details about symptoms, causes, and treatments, providing users with accurate and helpful information.



Index	Top-left X	Top-left Y	Bottom-right X	Bottom-right Y	Detection Accuracy	Disease
1	163	151	202	201	0.9596589207649231	Fillings
2	315	151	348	195	0.9513161182403564	Implant
3	297	154	319	198	0.9489832520484924	Fillings
4	136	145	173	189	0.9474994540214539	Fillings
5	338	102	363	143	0.944010317325592	Fillings
6	132	91	155	126	0.9411121606826782	Impacted Tooth
7	241	106	256	153	0.9309311509132385	Implant

Figure 5. DentistFree System Home Page.

#	Top-left X	Top-left Y	Bottom-right X	Bottom-right Y	Detection Accuracy	Disease
1	121	215	198	317	0.9233883023262024	Fillings
2	545	106	605	199	0.9182807207107544	Fillings
3	491	122	546	204	0.9157055616378784	Fillings
4	62	200	136	294	0.913887083530426	Fillings
5	552	210	601	311	0.9094873666763306	Implant
6	468	233	504	338	0.8888595700263977	Implant
7	436	239	470	341	0.8866958618164062	Fillings
8	501	221	554	290	0.8754315972328186	Fillings
9	199	127	232	213	0.8135668039321899	Fillings
10	148	102	205	197	0.8006587624549866	Fillings
11	92	97	153	191	0.6754807233810425	Fillings
12	92	98	153	192	0.4582720100879669	Implant

Figure 6. DentistFree System Result Page.

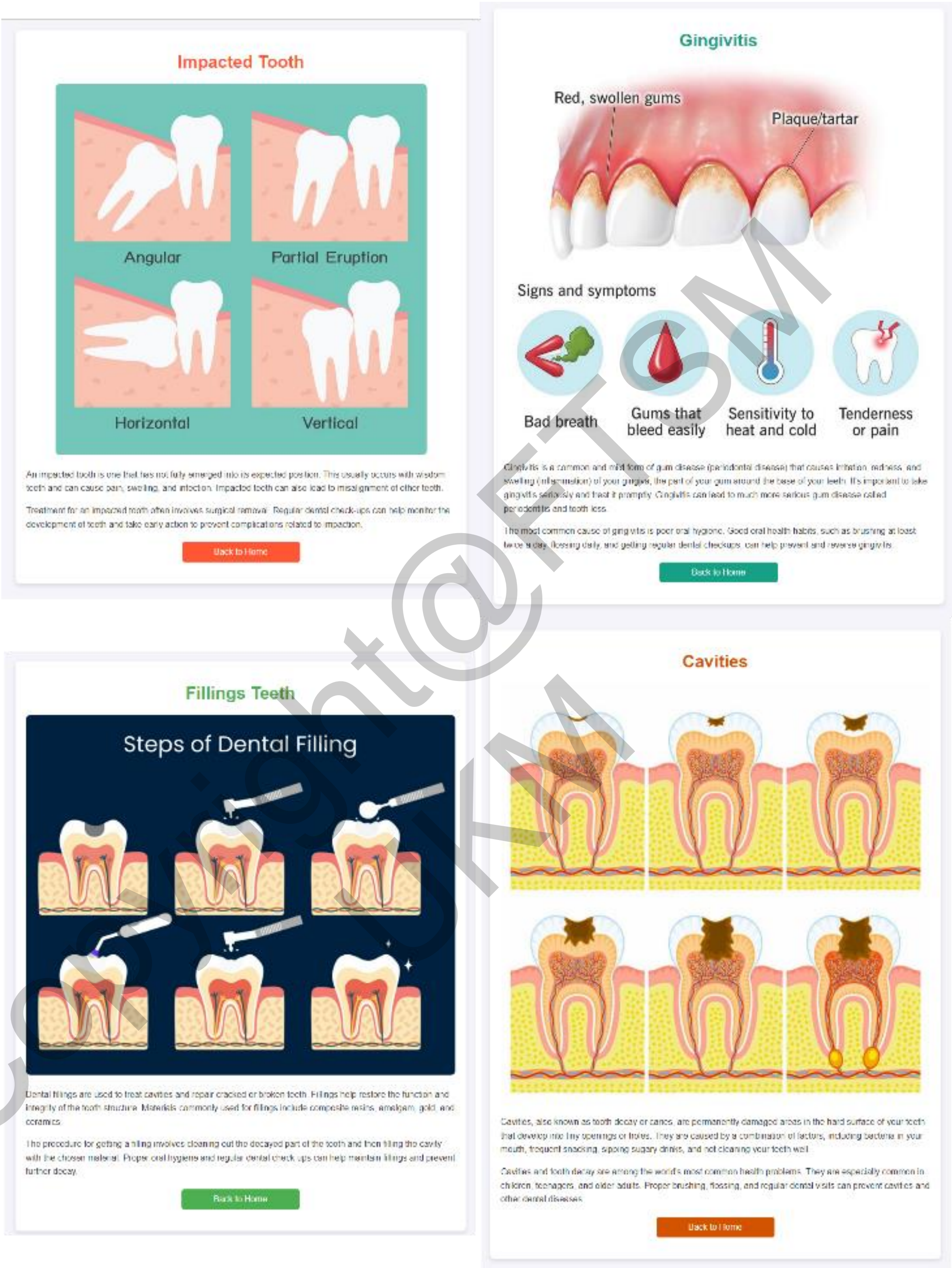


Figure 7. DentistFree System Specific Disease Information Pages.

Figure 8. DentistFree System Specific Disease Information Pages.

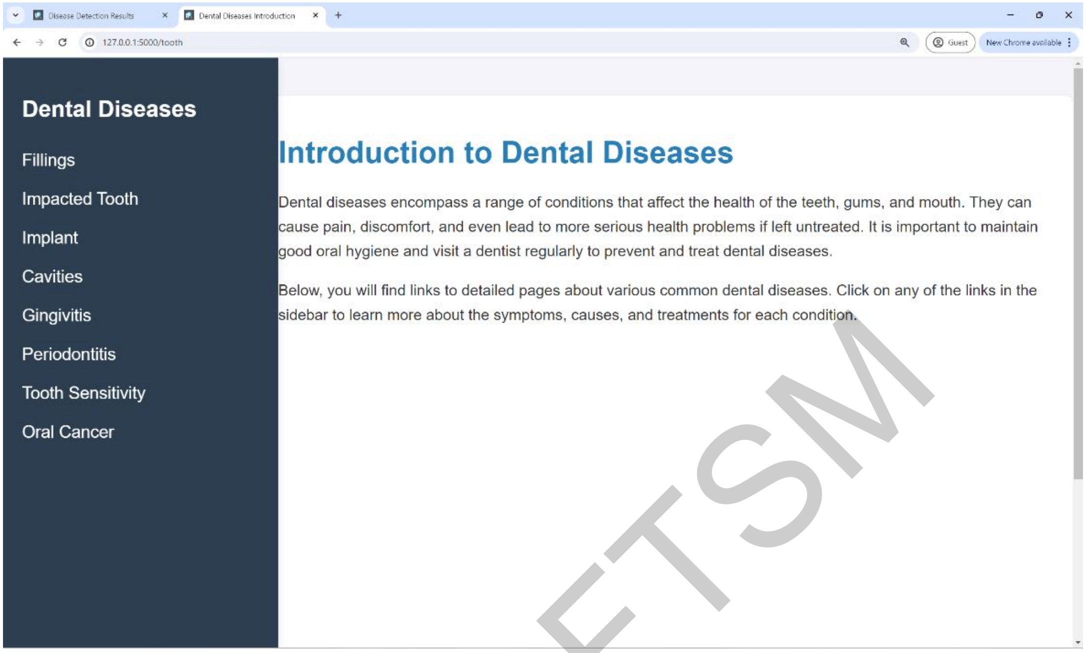


Figure 9. DentistFree System Disease Information Home Page.

3. Results and Discussion

Three components of the DentistFree System showed successful results during testing. Unit testing confirmed precise detection with coordinates and accuracy metrics, ensuring dental X-ray images were uploaded and displayed correctly. System testing verified the complete workflow's reliability, from image upload to result display and data retrieval, by simulating real-world scenarios. User Acceptance Testing (UAT) with dentists and dental students provided positive feedback on usability and detection accuracy, with minor improvement suggestions. The system's high accuracy (0.97) and reliability indicate it's ready for deployment, supporting dental disease detection and analysis.

Future work could focus on refining the model structure and exploring new data augmentation techniques to improve accuracy, especially for underperforming classes. Increasing the diversity and size of the dataset could enhance performance by allowing the model to learn from a wider variety of examples, improving its ability to detect and diagnose a broader range of dental diseases. Implementing user authentication with a login system could provide added security, ensuring only authorized users access the system and protecting patient information. Adding more dental diseases and features, such as treatment recommendations or integration with electronic health records, would make the system more valuable in clinical settings by providing actionable insights and easy access to patient records. Finally, developing a mobile app version could increase accessibility and convenience, allowing dentists and dental students to use the tool in various settings.

4. Conclusion

The DentistFree System is an advanced tool for dental diagnostics, using the YOLOv5 model and data augmentation techniques like Cutout and Mosaic to improve the detection of dental diseases from radiographic images. This system provides accurate diagnostic results and a smooth user experience through its web interface. By excluding the cavity class based on performance metrics and comparing it with Faster-RCNN, the effectiveness of the YOLOv5 model is highlighted. Future efforts will focus on improving the model and refining the system for better use in clinical settings. The DentistFree System demonstrates the potential of combining AI models with user-friendly web systems to enhance dental diagnostics, leading to better patient outcomes and increased dental health awareness.

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BORANG PENYERAHAN LAPORAN ILMIAH

SEM 2 SESI 2023 / 2024

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Tajuk Projek (*Project Title*):

Development of An Automated Dental Radiography Analysis System Using Yolo For The Detection of Dental Diseases

Tandatangan (*Signature*): YANG YUE Tarikh (*Date*): 16/7/2024

Bahagian B: Perakuan Penyelia
Part B: Supervisor's Approval

Saya peraku laporan ini telah disemak dan dibaiki, dan **menyokong / tidak menyokong*** penyerahan laporan ilmiah ini.
I certify that this report has been reviewed and amended, and ***approved / rejected**** *the report submission.*

Tandatangan (*Signature*): Tarikh (*Date*): 16/7/2024

Cap Rasmi:
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