BASIC PRINCIPLES AND REQUIREMENTS OF DENTAL DISEASE DETECTION SYSTEMS. RESEARCH OF RECOGNITION ALGORITHMS.

Temirova Xosiyat Farxod qizi,[1] Husanov Urol Abdumannon o'g'li[2]
[1,2] *assistant teacher*
[1,2] *"Tashkent University of Information Technologies", Tashkent, Uzbekistan.*
Xosiyattemirova6033@mail.ru
Phone: +998977816033

Abstract: Oral diagnosis simply refers to the analysis of the inside of the mouth. Effective treatment of any oral disease is possible only if a correct and accurate diagnosis is made. Oral diagnosis in the field of dentistry involves the examination and detection of all problems inside and outside the oral cavity, as well as finding the relationships between them, using scientific knowledge. Thus, it helps to formulate a final accurate treatment plan based on the findings collected. Effective treatment of any dental problem requires an accurate diagnosis. Diagnosis involves gathering information by collecting analysis and conducting a clinical examination of the patient. This is confirmed by using various diagnostic tools, and more accurate and detailed information is obtained from these diagnostic tools.

Keywords: Diagnosis, internal analysis, Dentistry, effective treatment, treatment plan, Dental diseases.

Introduction

Oral diagnosis simply refers to the analysis of the inside of the mouth. Effective treatment of any oral disease is possible only if a correct and accurate diagnosis is made. Oral diagnosis in the field of dentistry involves the examination and detection of all problems inside and outside the oral cavity, as well as finding the relationships between them, using scientific knowledge. Thus, it helps to formulate a final accurate treatment plan based on the findings collected. Effective treatment of any dental problem requires an accurate diagnosis. Diagnosis involves gathering information by collecting analysis and conducting a clinical examination of the patient. This is confirmed by using various diagnostic tools, and more accurate and detailed information is obtained from these diagnostic tools.

The tools and algorithms used in the diagnosis of dental diseases are developed based on a number of important principles and requirements. These principles and requirements are listed below.

Accuracy and Reliability Accuracy Diagnosis must be accurate. Algorithms must have high accuracy in accurately identifying diseases. Diagnoses must be reproducible and produce the same results under different conditions.Fast Analysis The analysis process must be fast, which is important for doctors and patients. Getting fast results speeds up medical decisions. Efficiency Anlysis algorithms must require few resources and work efficiently. This is especially important in limited environments.Re-learning ability Algorithms must adapt to new information and update themselves. This is important in the learning process.Interface Provide a user-friendly interface. It should be easy to use and understandable for doctors and medical staff.The requirements for dental disease detection tools and algorithms are significant. It is necessary to take into account such principles as high accuracy, speed, efficiency and ease of use. In the process of analyzing recognition algorithms, convolutional neural networks, transfer learning, segmentation and traditional machine learning methods play an important role. These tools and methods increase the efficiency of medical image analysis.

Related works

Object recognition algorithms include the following. Object detection is an important and challenging area of computer vision and has been the subject of extensive research [1]. The goal of object detection is to detect all objects and classify them. It has been widely used in autonomous driving [2], pedestrian detection [3], medical imaging [4], industrial detection [5], robot vision [6], intelligent video surveillance [7], and remote sensing images [8]. In recent years, deep learning methods have been applied to object recognition [9]. Deep learning uses low-level features to form more abstract high-level features and hierarchically represent data to improve object recognition [10]. Compared with traditional recognition algorithms, object recognition methods based on deep learning have better performance in terms of robustness, accuracy, and speed for many classification tasks. YOLO (You Only Look Once) This algorithm allows for fast object detection in real time. Newer versions of the YOLO algorithm (YOLOv3, YOLOv4, YOLOv5) are widely used in the field of computer vision and object detection.

Faster R-CNN (Faster Region-based Convolutional Neural Network): This algorithm is used for object detection and classification. It determines the location and type of the object. Faster R-CNN is one of the widely used algorithms. SSD (Single Shot MultiBox Detector) This algorithm quickly detects an object and determines its location. In the SSD algorithm, object detection and location determination are performed simultaneously.

Mask R-CNN This algorithm is used for object dction and segmentation. Mask R-CNN not only de object, but also detects its contour.

RetNet This algorithm is used for object detection and its location. Unlike other algorithms, RetNet works well in cases where there is a large difference between objects.

Viola-Jones algorithm This algorithm is used to detect faces and other objects. It is designed to run in a short time.The above algorithms are among the most widely used algorithms in the field of computer vision and object recognition. They are used for various tasks, such as object detection, localization, segmentation, and classification.Among the analyzed algorithms, the most effective algorithm for object recognition is the Yolo model.

III. method. YOLO (You Only Look Once) Fast Object Detection Algorithm. Object detection is a computer vision task that involves identifying and locating objects in images or videos. It is an important part of many applications such as surveillance, self-driving cars, or robotics. Object detection algorithms can be divided into two main categories: one-shot detectors and two-shot detectors. Object detection algorithms are divided into two categories based on the number of times the same input image is transmitted over the network.

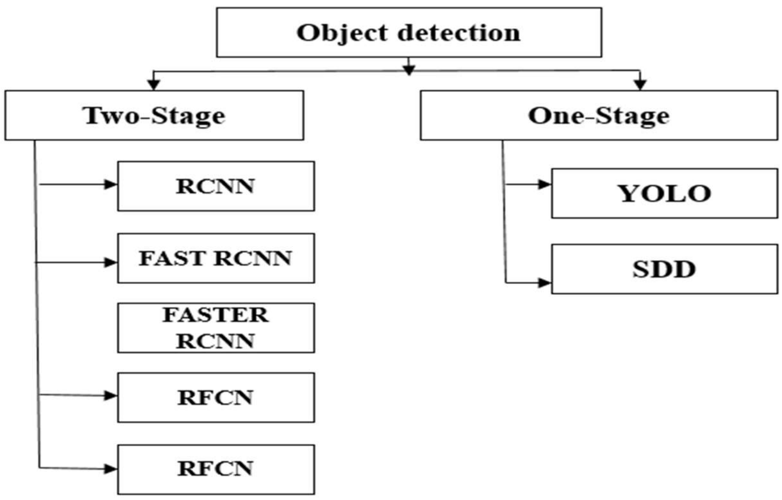

Figure 1. Block diagram of single-stage.

Single-pass object detection uses a single pass of the input image to predict the presence and location of objects in the image. It processes the entire image in a single pass and is efficient in counting them. However, single-pass object detection is generally less accurate than other methods and is not as effective at detecting small objects. Such algorithms can be used for real-time object detection in resource-constrained environments.[11].

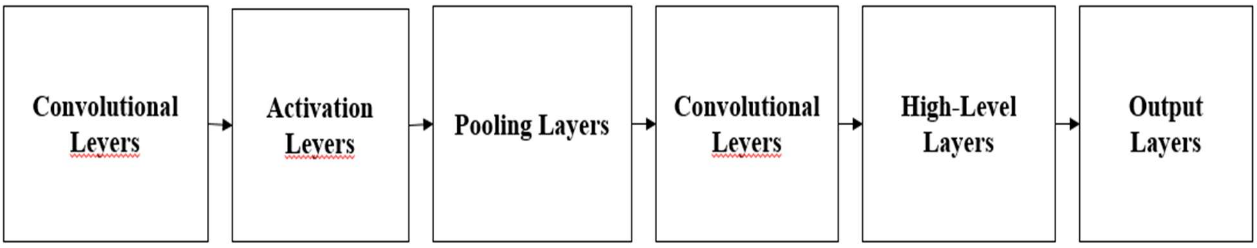

Figure 2. General Yolo architecture.

The YOLO (You Only Look Once) algorithm has developed different versions, each with its own advantages and disadvantages. The YOLO v1 model has the advantages of real-time operation, simple architecture, easy understanding and implementation. It has disadvantages such as errors in detecting small objects and close objects, limited location accuracy, and uncertainty in detecting square lines.

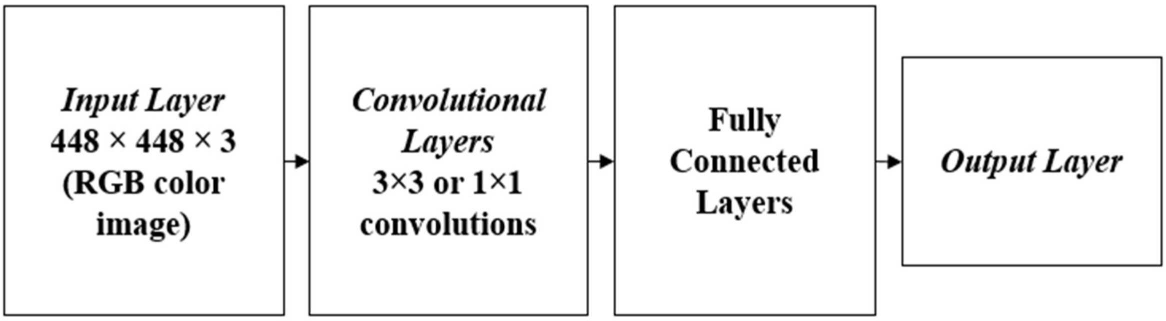

Figure 3. Yolo v1 model architecture.

YOLOv2 (YOLO9000) Improved accuracy Improved accuracy compared to YOLOv1, Multi-scale training, Ability to train on images of different sizes, More objects to learn Can detect more than 9000 objects. Complexity This is a disadvantage of the Yolo v2 model, which has a more complex architecture than YOLOv1.

Feature	YOLOv1	YOLOv2
Number of convolutional layer	24 convolutional layers + 2 Fully Connected layers	19 convolutional layers + 5 MaxPooling layers
Fully Connected Layers	Used to give the coordinates of a bounding box	Fully connected layers removed (for clarity)
Input image size	448 × 448	416 × 416 (for more flexibility)
Bounding Box Generator	The coordinates of the box are directly taught.	Anchor Box concept introduced
Output volume	S × S × (B × 5 + C) (dependent on bounding box)	S × S × (B × (5 + C)) (using anchors)
Activation function	ReLU	Leaky ReLU (works better on deeper networks)
Object types (classes)	There are restrictions on determining the number of objects	The number of classes is increased and flexible

Figure 4. Yolo v1 and Yolov2 model comparison analysis.

The Yolo v2 object detector uses a single-stage object detection network. The Yolo v2 is faster than two-stage deep learning object detectors such as regions with convolutional neural networks (Faster R-CNNs). The Yolo v2 model learns the CNN deeply on the input image to produce network predictions. The object detector decodes the predictions and generates bounding boxes[12]. There are a number of important differences between Yolo v1 and Yolo v2. Below are the layers of each version and their differences.The Yolo v1 model accepts a 448x448 pixel image input in the input layer, while the Yolo v2 model accepts a 416x416 pixel input layer.

The Yolo v1 model consists of 24 convolutional layers in the convolutional layer. The Yolo v2 model uses 19 convolutional layers, 1x1 layers.In the pooling layer, the Yolo v1 model uses traditional max pooling layers. In the Yolo v2 model, the locations of the Pooling layer have been changed.

The output layer of the Yolo v1 model uses a 7X7 grid, with 2 squares in each grid. In the Yolo v2 model, it uses a 13x13 grid, with 5 squares in each grid.The main advantages of the Yolo V2 model over the Yolo v1 model are its improved accuracy and speed.

High detection efficiency Yolo v2 can run on less powerful edge devices, but it also has the disadvantage of not being able to detect small objects.[54] Yolo v3 model performance is improved in detecting objects at long distances, high accuracy in detecting large and small objects, using Darknet-53 architecture, fast and efficient feature extraction, multiple output levels, high accuracy in detecting objects of different sizes. Disadvantages Slightly slower than Yolo v2, resource-intensive, requires more computing power and memory.

There are significant differences between Yolo v3 and older versions in terms of speed, accuracy, and class specificity. Yolo v2 and Yolo v3 differ in terms of accuracy, speed, and network architecture. Yolo v2 was released in 2016, two years before Yolo v3.[13] Advantages of Yolo v4 model Learning speed, faster learning compared to Yolo v3, Accuracy, another step forward, uses several new techniques, balances speed and accuracy, has high accuracy in real time. Disadvantages Complexity, increased complexity due to new layers and techniques added, requires more time to train.

The main differences between the Yolo v3 and Yolo v4 models are in the architecture. The Yolo v3 model uses the Darknet-53 architecture, while the Yolo v4 model uses the CSPDarknet-53 architecture, which improves the efficiency of the model. In the convolutional layer, the Yolo v3 model has 53 convolutional layers, mainly 3x3 and 1x1 layers, while the Yolo v4 model has 24 convolutional layers, but there are CSP and new layers added. The activation functions are the ReLU activation function in the Yolo v3 model, and the Mish activation function in the Yolo v4 model, which improves the learning process. Efficiency High speed in the Yolo v3 model, but poor accuracy, Improved speed and accuracy in the Yolo v4 model, improved to extract more features.

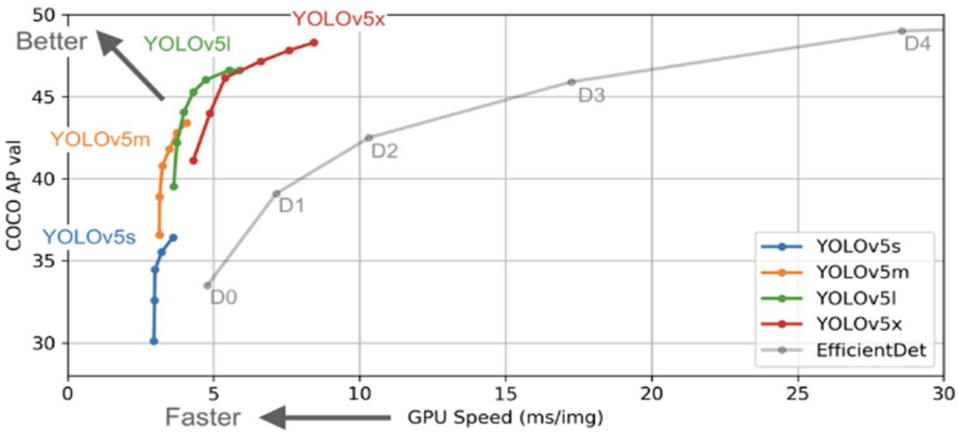

Figure 6. Evaluating object recognition of the Yolo v5 model.

The differences between YOLOv3 and YOLOv4 are evident in the layer structure, architecture, and performance. YOLOv4 offers improved accuracy and speed over YOLOv3 with newly added layers and optimizations, which allows for more efficient object detection. Yolo v4 is a powerful and efficient object detection model that balances speed and accuracy. Yolo v4 can be trained and used by anyone with a simple GPU computer, making it suitable for a wide range of applications [56]. Advantages of the Yolo v5 model: Easy implementation, written in PyTorch and user-friendly, lightweight model, fast performance and low resource requirements, automatic training and optimization, more flexibility in the model learning process, disadvantages: There are some problems with detecting small objects.

The Yolo v5 model can process images several times faster than the EfficientDet Yolo v4 model[14].The Yolo v5 and Yolo v6 models are efficient and fast convolutional neural networks for object detection. Each version has its own layer structure and optimizations. The main differences are listed below.

The main differences are that the Yolo v5 model uses the Darknet architecture in its architecture. The Yolo v6 uses an architecture supplemented with CSP layers and new optimizations. Convolutional layers The Yolo v5 model has 46 convolutional layers, the Yolo v6 model has 35 convolutional layers, but with more efficient designs. In the Pooling and Activation layers, the Yolo v5 model uses Max pooling and average pooling, while the Yolo v6 model uses optimized pooling layers, while the Yolo v5 model is fast, but has errors in detecting some objects.

Yolo v6 model advantages CSP Layer Efficient data transfer and reduce computational burden, RepConv layer More efficient feature extraction through Reparameterized Convolution layer. High accuracy Improved in detecting large and small objects. Speed optimized Architecture, enables fast performance, Efficient Layer Design, layer design for increased speed. Flexibility, Data Augmentation, Strengthen the model in different conditions. Automatic Training, Automatic model selection and training options are available.

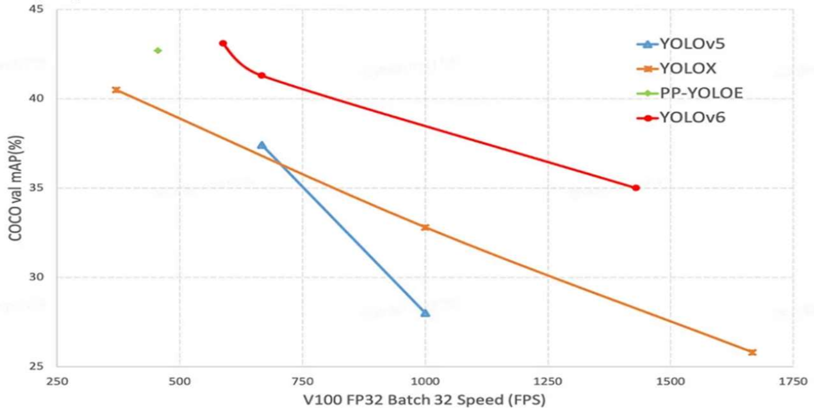

Figure 7. Yolo v6 model performance test.

The Yolo v6 model is an improvement over the previous Yolo v5 model, with a 51% improvement in speed compared to the detectors [15].

The Yolo v7 model operates at high speed, making it ideal for real-time object detection. The model's performance has also been improved. Yolo v7 shows high accuracy in detecting many objects at the same time. This makes the model reliable even in complex scenes, and the model is able to work with high-dimensional images, which increases accuracy. Yolo v7 is easy to adapt to various data sets, which allows it to be used in many different tasks. The model architecture is modular, which can be easily extended and modified, Yolo v7 allows the use of existing models during the training process, which saves time for new tasks, and supports advanced methods using new technologies and algorithms, which increases the overall efficiency of the model.

Comparison of YOLOv7 and YOLOv6 Compared to the previous most accurate YOLOv6 model (56.8% AP), the YOLOv7 real-time model achieves 13.7% higher AP (43.1% AP) on the COCO dataset.

Comparing the lighter Edge model versions on the COCO dataset under the same conditions (V100 GPU, batch=32), YOLOv7-tiny is more than 25% faster, achieving a slightly higher AP (+0.2% AP) than YOLOv6-n.[16].

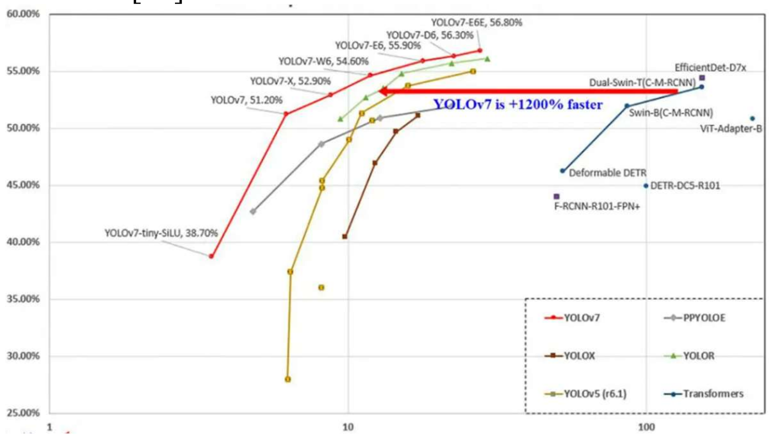

Figure 8. Yolo v8 model performance test.

The Yolo v8 model is the latest version of the YOLO (You Only Look Once) family of models, and offers a number of new features and improvements. With high accuracy, Yolo v8 can detect objects more accurately and quickly, which helps it work efficiently even in complex scenes. This model provides high accuracy while maintaining speed, which is useful for real-time work. The new architecture YOLOv8 is known for its updated architecture, which includes more efficient features and allows for more efficient use of computing resources. The model can be easily adapted to existing datasets, which saves time for new tasks. Yolo v8 has a modular structure, allowing users to modify and optimize the model according to their needs. The model is able to work effectively with high-dimensional images, which increases accuracy. Yolo v8 comes with many new features and capabilities, including expanded support for analyzing new images and videos. This model can be easily integrated into existing systems or applications.

Yolo v9 uses Yolo v7 as the base model and improves upon it. Yolo v9 introduces four important concepts, namely programmable gradient input (PGI), generalized efficient layer aggregation network (GELAN), data blocking principle, and recursive functions. YOLOv9 now has the capabilities of object detection, segmentation, and classification.

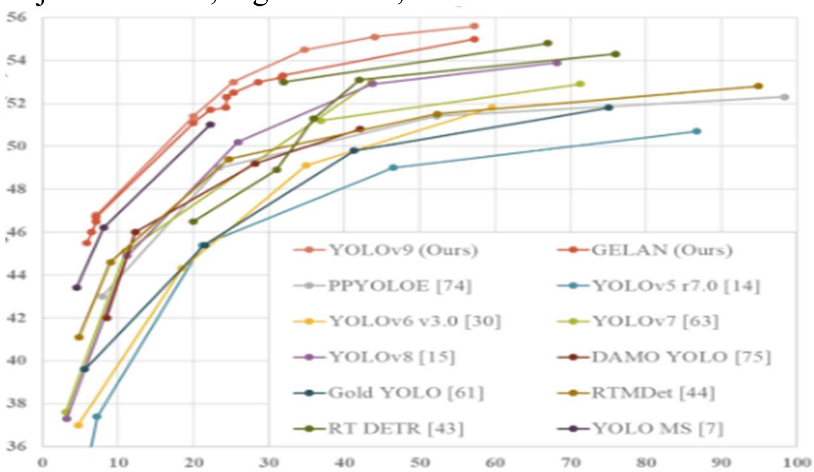

Figure 9. Yolo v9 model performance test.

In general, among the available methods, YOLO MS-S for lightweight models, YOLO MS for medium models, YOLOv7 AF for general models, and YOLOv8-X for large models are the most efficient methods. Compared to YOLO MS for lightweight and medium models, YOLOv9 has about 10% fewer parameters and requires 5-15% fewer computations, but it still shows a 0.4-0.6% improvement in Average Accuracy (AP). Compared to YOLOv7 AF, YOLOv9-C has 42% fewer parameters and 22% fewer computations, while maintaining the same AP (53%). Finally, compared to YOLOv8-X, YOLOv9-E has 16% fewer parameters, 27% fewer computations, and a significant improvement in AP of 1.7%. In addition, an ImageNet pre-trained model is also included for comparison, and it is based on the parameters and the amount of computation the model takes. RT-DETR showed the best result considering the number of parameters.

Combining PGI and GELAN in the YOLOv9 design shows strong competitiveness. With this combination, YOLOv9 is able to reduce the number of parameters by 49% and the number of calculations by 43% compared to YOLOv8. Despite these reductions, the model still achieved an average accuracy improvement of 0.6% on the MS COCO dataset [17].The computational complexity of the Yolo v9 model increases with increasing data, and the ability of the new model to adapt to different environments and tasks is limited compared to the previous versions. The shortcomings of the Yolo v9 model are that there is room for further improvement of the model.

When experimenting with the Yolo v9 model on the detection of cavities from dental X-ray images, the following results were obtained.

The proposed model algorithm is shown below (Fig-1).

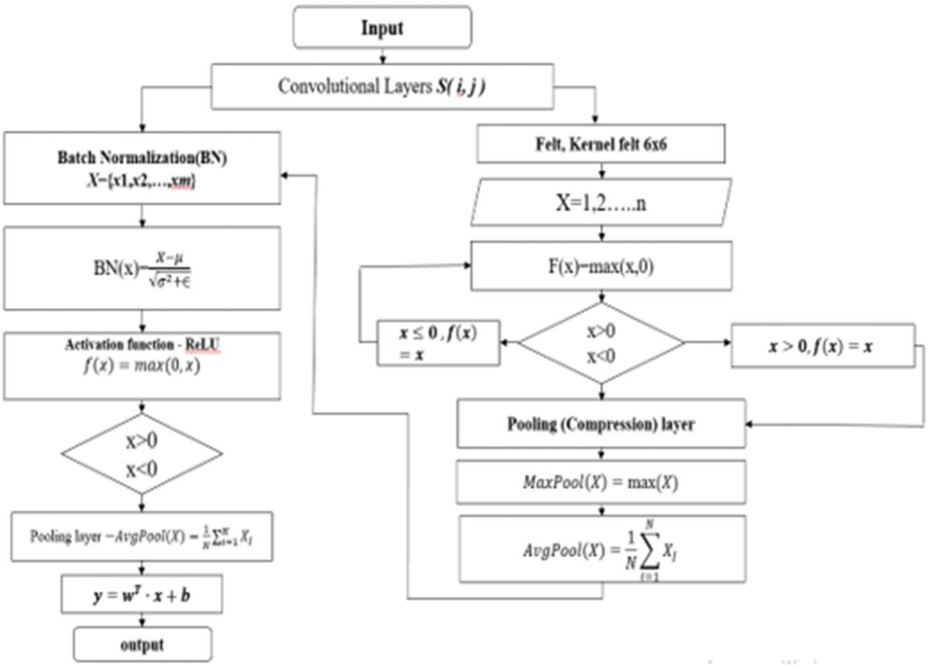

Figure 10. proposed algorithm.

Experimental results. To identify dental diseases from dental X-ray images, a data set of dental X-ray images of healthy teeth, dentures, gums, and pulp disease was formed (Table 1).

Tablet 1. collection of structured data from dental X-ray images to detect dental diseases.

№	train	validation	test
1	137	68	68

The figure below shows the results obtained from the above dataset based on the proposed model. (Figure 10)

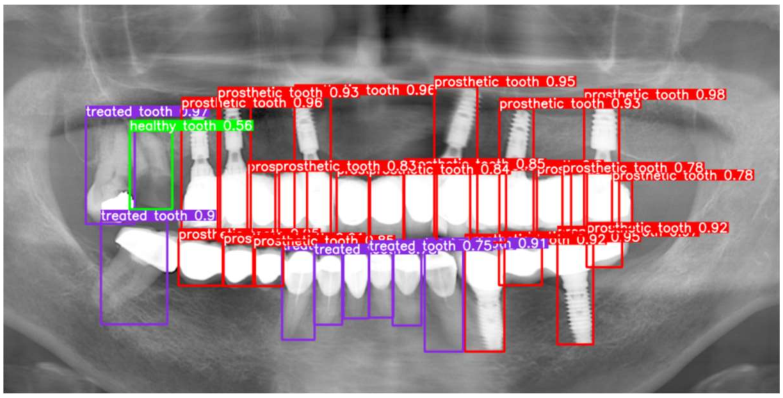

Figure 11. Dental X-ray image diagnosis.

When trained using the above database using the Yolo v9 model, it produced the above result.

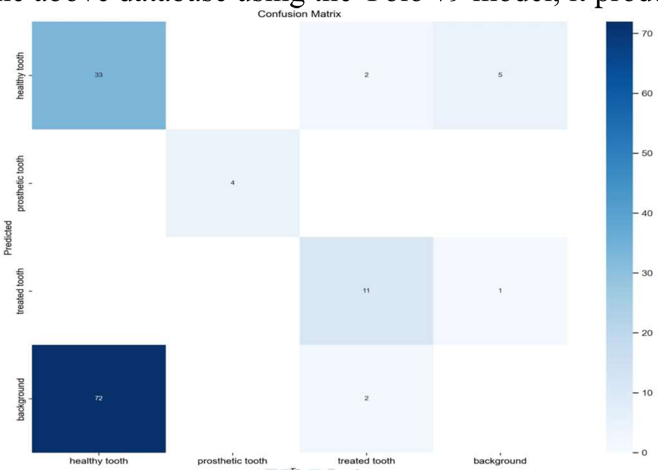

Figure 12. Model performance accuracy.

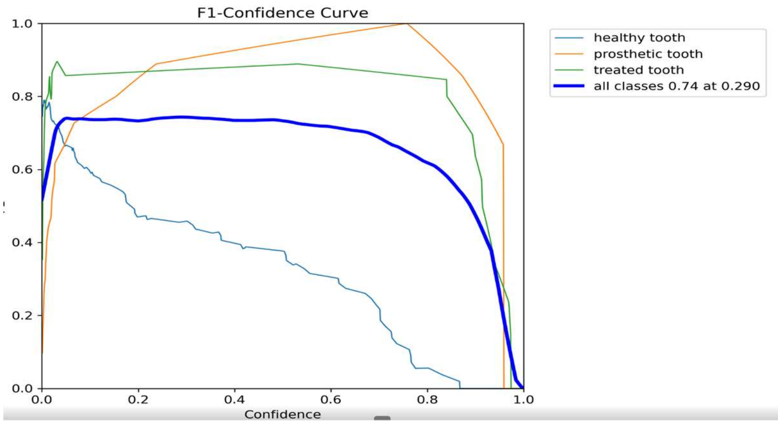

Figure 13. F1 error of the model.

CONCLUSION

Oral diagnosis simply refers to the analysis of the inside of the mouth. Effective treatment of any oral disease is possible only if a correct and accurate diagnosis is made. Oral diagnosis in the field of dentistry involves the examination and detection of all problems inside and outside the oral cavity using scientific knowledge, as well as finding the relationships between them. Thus, it helps to formulate a final accurate treatment plan based on the findings collected. Effective treatment of any dental problem requires an accurate diagnosis. Diagnosis involves gathering information by collecting an analysis and conducting a clinical examination of the patient. This is confirmed by using various diagnostic tools, and more accurate and detailed information is obtained from these diagnostic tools. The most effective model for detecting dental diseases from X-ray dental images using the algorithms and models analyzed above is the Yolo v9 model, which has much better accuracy than the Yolo v8 model, and its performance speed has also improved significantly.

REFERENCES

1. H. Ge, Y. Shi, M. Zhang, Y. Wei, H. Zhang and X. Cao, "YOLO: An Improved High-Accuracy Method for PCB Defect Detection," 2024 IEEE 12th International Conference on Computer Science and Network Technology (ICCSNT), Dalian, China, 2024, pp. 159-165, doi: 10.1109/ICCSNT62291.2024.10776686.
2. Mekhriddin Rakhimov, Dilnoza Zaripova, Shakhzod Javliev, Jakhongir Karimberdiyev; Deep learning parallel approach using CUDA technology. AIP Conf. Proc. 27 November 2024; 3244 (1): 030003. https://doi.org/10.1063/5.0241439.
3. M. Rakhimov, R. Akhmadjonov and S. Javliev, "Artificial Intelligence in Medicine for Chronic Disease Classification Using Machine Learning," 2022 IEEE 16th International Conference on Application of Information and Communication Technologies (AICT), Washington DC, DC, USA, 2022, pp. 1-6, doi: 10.1109/AICT55583.2022.10013587.
4. Rakhimov, M., Karimberdiyev, J., Javliev, S. (2024). Artificial Intelligence in Medicine: Enhancing Pneumonia Detection Using Wavelet Transform. In: Choi, B.J., Singh, D., Tiwary, U.S., Chung, WY. (eds) Intelligent Human Computer Interaction. IHCI 2023. Lecture Notes in Computer Science, vol 14531. Springer, Cham. https://doi.org/10.1007/978-3-031-53827-8_16
5. Goran Oreski. 2023. YOLO*C — Adding context improves YOLO performance. Neurocomput. 555, C (Oct 2023). https://doi.org/10.1016/j.neucom.2023.126655
6. M. Rakhimov, J. Elov, U. Khamdamov, S. Aminov and S. Javliev, "Parallel Implementation of Real-Time Object Detection using OpenMP," 2021 International Conference on Information Science and Communications Technologies (ICISCT), Tashkent, Uzbekistan, 2021, pp. 1-4, doi: 10.1109/ICISCT52966.2021.9670146.
7. Nasimov, R., Rakhimov, M., Javliev, S., Abdullaeva, M. (2024). Parallel Approaches to Accelerate Deep Learning Processes Using Heterogeneous Computing. In: Koucheryavy, Y., Aziz, A. (eds) Internet of Things, Smart Spaces, and Next Generation Networks and Systems. NEW2AN ruSMART 2023 2023. Lecture Notes in Computer Science, vol 14543. Springer, Cham. https://doi.org/10.1007/978-3-031-60997-8_4.
8. Mekhriddin Rakhimov, Shakhzod Javliev, and Rashid Nasimov. 2024. Parallel Approaches in Deep Learning: Use Parallel Computing. In Proceedings of the 7th International Conference on Future Networks and Distributed Systems (ICFNDS '23). Association for Computing Machinery, New York, NY, USA, 192–201. https://doi.org/10.1145/3644713.3644738
A. Thulaseedharan and L. P. P. S, "Deep Learning based Object Detection Algorithm for the Detection of Dental Diseases and Differential Treatments," 2022 IEEE 19th India Council International Conference (INDICON), Kochi, India, 2022, pp. 1-7, doi: 10.1109/INDICON56171.2022.10040109.
9. Wang, M.; Yang, B.; Wang, X.; Yang, C.; Xu, J.; Mu, B.; Xiong, K.; Li, Y. YOLO-T: Multitarget Intelligent Recognition Method for X-ray Images Based on the YOLO and Transformer Models. Appl. Sci. 2022, 12, 11848. https://doi.org/10.3390/app122211848.
10. Otabek Ismailov, Xosiyat Temirova; Tooth square detection using artificial intelligence. AIP Conf. Proc. 27 November 2024; 3244 (1): 030030. https://doi.org/10.1063/5.0242591
11. Terven, J.; Córdova-Esparza, D.-M.; Romero-González, J.-A. A Comprehensive Review of YOLO Architectures in Computer Vision: From YOLOv1 to YOLOv8 and YOLO-NAS. Mach. Learn. Knowl. Extr. 2023, 5, 1680-1716. https://doi.org/10.3390/make5040083.
12. Davron Ziyadullaev, Dildora Muhamediyeva, Sholpan Ziyaeva, Umirzoq Xoliyorov, Khasanturdi Kayumov, Otabek Ismailov. "Development of a traditional transport system based on the bee colony algorithm". E3S Web of Conf. 365 01017 (2023). DOI: 10.1051/e3sconf/202336501017.

13. R. Mohan, R. Arunmozhi and V. Rajinikanth, "Deep-Learning Segmentation and Recognition of Tooth in Thresholded Panoramic X-ray," *2023 Winter Summit on Smart Computing and Networks (WiSSCoN)*, Chennai, India, 2023, pp. 1-5, doi: 10.1109/WiSSCoN56857.2023.10133861.
14. Suryani, D & Shoumi, M & Wakhidah, Rokhimatul. (2021). Object detection on dental x-ray images using deep learning method. IOP Conference Series: Materials Science and Engineering. 1073. 012058. 10.1088/1757-899X/1073/1/012058.
15. Abdusalomov, A.B.; Nasimov, R.; Nasimova, N.; Muminov, B.; Whangbo, T.K. Evaluating Synthetic Medical Images Using Artificial Intelligence with the GAN Algorithm. Sensors 2023, 23, 3440. https://doi.org/10.3390/s23073440
16. J. George, T. S. Hemanth, J. Raju, J. G. Mattapallil and N. Naveen, "Dental Radiography Analysis and Diagnosis using YOLOv8," 2023 9th International Conference on Smart Computing and Communications (ICSCC), Kochi, Kerala, India, 2023, pp. 102-107, doi: 10.1109/ICSCC59169.2023.10335023.