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Deployment of Web-Based YOLO for CT Scan Kidney Stone Detection

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Abstract: This research aims to develop a kidney stone object detection system using machine learning techniques like YOLO and object detection, integrated into a Flask-based web interface to support early diagnosis by medical professionals. The trained model demonstrates strong pattern learning capabilities. Evaluation of the public dataset model reveals an average mean Average Precision (mAP) of 0.9698 for 'kidney stone' labels. This detection model exhibits high performance with an accuracy rate of 96.33%, precision of 96.98%, recall of 99.23%, and an F1-score of 98.1%. Clinical data evaluation shows that the YOLOv5-based detection system performs exceptionally well, with an average mAP of 0.9571, accuracy of 93.06%, precision of 95.71%, recall of 97.1%, and F1-score of 96.49%, indicating the model's capability to detect kidney stones with high precision and accuracy. Thus, both the evaluation on the public dataset and clinical dataset performance support accurate diagnosis processes and further treatment planning. Moreover, this research advances to the stage where the detection model can be directly utilized through implementation via Flask web deployment.

Keywords: Kidney stones; Kidney CT-Scan; YOLO v5; Object detection; Flask Web Integration

INTRODUCTION

Kidney stone disease is a common health condition, especially among adults. Kidney stones are solid masses formed from crystals of minerals and salts that precipitate in the kidneys or urinary tract (Akkasaligar & Biradar, 2020). The formation process of these stones can cause pain and discomfort to the sufferers. Over time, undetected and untreated kidney stones can lead to various serious health problems (Aplikasi et al., 2022). Early detection of kidney stones plays a crucial role in preventing further complications. By detecting kidney stones quickly, appropriate treatment can be initiated promptly, preventing the possibility of urinary tract infections, kidney inflammation, or kidney tissue damage (Bagchi, 2022). Therefore, the implementation of accurate diagnostic methods becomes crucial in the management of kidney stone disease (Hatami et al., 2023).

In detecting kidney stones, several diagnostic methods commonly used include X-rays, which are effective for larger and denser stones, and ultrasonography (USG), which is safer but less sensitive to small stones. Additionally, MRI provides detailed images without radiation but is more expensive, while CT scans are considered most suitable due to their high accuracy, detailed three-dimensional imaging, speed, and high efficiency (Hoffman, 2021). CT scan images provide detailed information about the organs surrounding the kidneys, allowing clear identification of the location, size, and characteristics of the stones (Bagla et al., 2022). With an integrated object detection system, it is expected that the results from CT scan images can be interpreted more quickly and accurately by medical personnel, enabling them to respond promptly to patient conditions and provide appropriate care (Howles & Thakker, 2020).

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Thus, technological advancements in this field have great potential to have a positive impact on early diagnosis and treatment of kidney stone patients (Jha et al., 2022).

Several previous studies have proposed the use of machine learning technology, particularly YOLO (You Only Look Once) algorithms, in medical image object detection (Dawami et al., 2023). One recent relevant study is conducted by (Bagchi, 2022), which successfully implemented an object detection system using YOLO on CT scan images to detect abnormalities in specific organs. However, further development is needed by incorporating object detection techniques to make the object detection results more detailed and useful for medical professionals (Kavitha & Palaniappan, 2023).

The selection of YOLOv5 in this study is based on its superiority in terms of accuracy, speed, and computational efficiency (Pulipalupula et al., 2023). YOLOv5 outperforms previous versions in detection performance and is lighter and easier to implement across various hardware platforms (Lemay, 2019). Additionally, YOLOv5 is equipped with various new features that enhance overall object detection capabilities (Minaee et al., 2022). Therefore, YOLOv5 is chosen as the main algorithm for detecting kidney stones in CT scan images (Muhd Suberi, 2020).

Object detection is a technique in image processing aimed at dividing the image into several segments or parts that have certain characteristics or attributes (Fan & Fan, 2023). The main goal of object detection is to understand the structure and content of the image in more detail, by identifying and separating specific areas or objects in the image (Nugraha & Sipayung, 2023). In the context of this research, object detection is used to focus the analysis on specific areas in CT scan images related to kidney stone disease (Pattanayak, 2023). By performing this object detection, more detailed and specific information about the location and size of kidney stones can be obtained, increasing the accuracy in the object detection process (Indaryanto et al., 2021).

YOLO (You Only Look Once) is an approach in deep learning used for object detection in images (Pranovich et al., 2022). This method views object detection as a regression problem solved by convolutional neural networks (CNN) directly, enabling faster and more accurate object detection (Rathod & Trivedi, 2021). In this research case, YOLO is used to detect the presence of kidney stones in CT scan images. The advantage of YOLO lies in its ability to efficiently detect objects in images with a single feedforward process, making it suitable for implementation in image object detection systems that require rapid response (Ferraro et al., 2023). In this study, clinical (private) data was also tested to ensure that the system can work with real patient data (Relan, 2019).

Integrating object detection techniques with YOLO algorithms in CT scan image analysis aims to obtain more detailed and accurate information about their location, size, and characteristics (Gothane, 2021). Object detection focuses on analyzing relevant areas in the image, while YOLO is used to detect the presence of kidney stones in those areas (Vysakh V Mohan et al., 2022). The combination of these two techniques is expected to improve object detection results by providing more informative and accurate information (Wibowo et al., 2023). The synergy between object detection and YOLO enhances the system's ability to identify and understand information in CT scan images related to kidney stones. This step is considered crucial in developing a system that can positively contribute to the effectiveness of diagnosing and treating kidney stone disease, as well as assisting medical professionals in clinics or hospitals (Yudha Sambawitasia et al., 2022).

Providing object detection results through a web interface using Flask will facilitate medical personnel in accessing and understanding disease diagnoses in CT scan images (Dwiyanto et al., 2022).

LITERATURE REVIEW

The research detailed in the journal titled "Helmet Use Detection with Deep Learning Techniques" leverages advancements in deep learning technology, specifically YOLOv5, to detect helmet use at Universitas Diponegoro. According to data from Korlantas Polri in November 2023, 83.50% of the 158.90 million motor vehicles in Indonesia are motorcycles, contributing significantly to the high rate of traffic accidents. Data from the Central Statistics Agency in 2021 reported 103,645 traffic accidents, with 73% involving motorcycles. Universitas Diponegoro faces a similar challenge with many riders failing to comply with helmet regulations. Various methods, including Haar Cascades, thresholding, and CNN (Batubara et al., 2024), have been proposed for helmet detection; however, YOLOv5 offers superior accuracy and speed. Using a dataset consisting of 1,588 images and various augmentation

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techniques, the trained YOLOv5 model achieved an mAP of 0.938 and a system accuracy of 98.5%. Integration with an Android application allows for real-time monitoring and enforcement of helmet regulations on campus, providing a practical solution to enhance safety in an educational environment.

The advantages of YOLOv5 in terms of speed, accuracy, and computational efficiency make it a suitable choice for this task. Object detection techniques enable the system to more accurately determine the location of kidney stones, thus aiding medical professionals in prompt diagnosis and treatment. The successful application of YOLOv5 for helmet use detection demonstrates the significant potential of this algorithm for similar applications in the medical field. The combination of object detection and YOLO algorithms offers a promising approach to improving the accuracy of diagnosing and managing kidney stone disease, ultimately benefiting patients and healthcare providers. Providing object detection results through a user-friendly web interface further enhances the accessibility and interpretation of diagnoses from CT scan images, improving clinical workflow and patient care.

METHOD

The methodology flowchart used in this research is shown below.

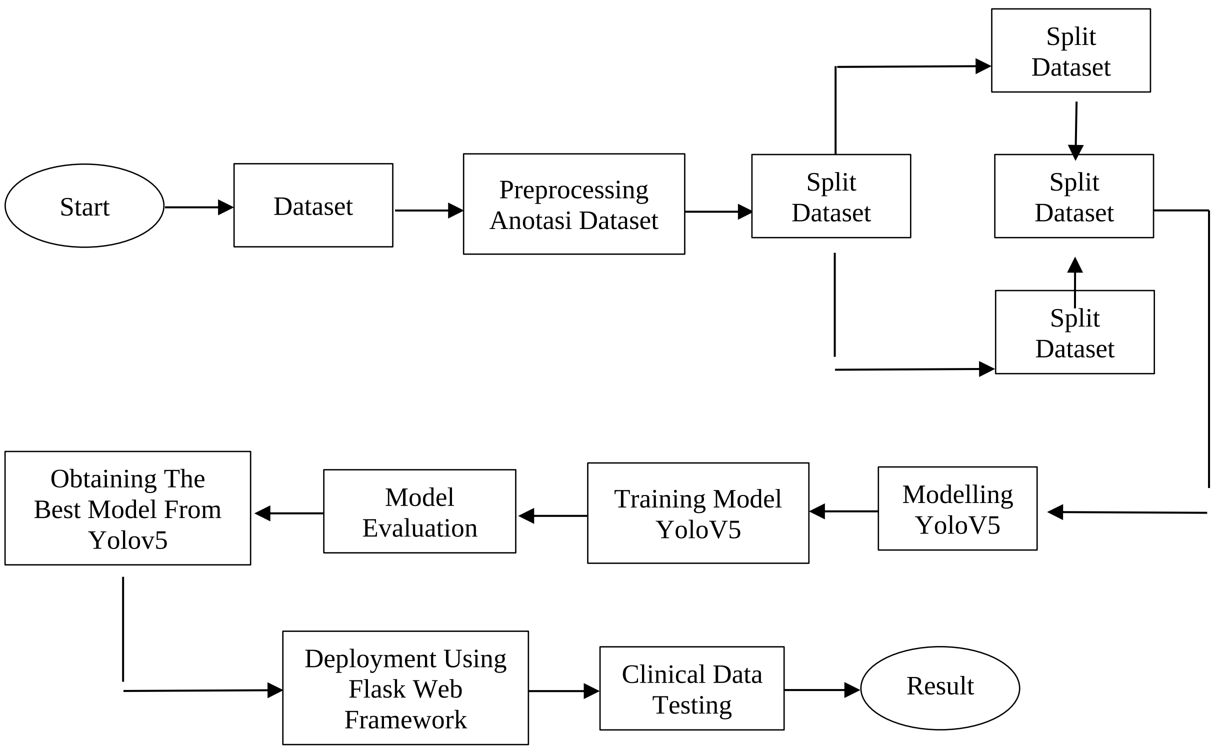

Fig. 1 Research Stages

Dataset

In this research, the researchers collaborated with radiographers or medical institutions to obtain access to kidney CT scan datasets. The study involved the role of radiographer Isa Faiz Muammar (NIR 3374231222097) from Bhayangkara AKPOL Hospital Semarang in the annotation and validation process. This research only processed private kidney datasets for patients diagnosed with kidney stone disease, obtained from RSUD Kebumen and RS Sultan Agung Semarang. These clinical datasets are in JPG and JPEG formats, totaling 716 images, and this study used a sample of 10% of the total clinical or private dataset.

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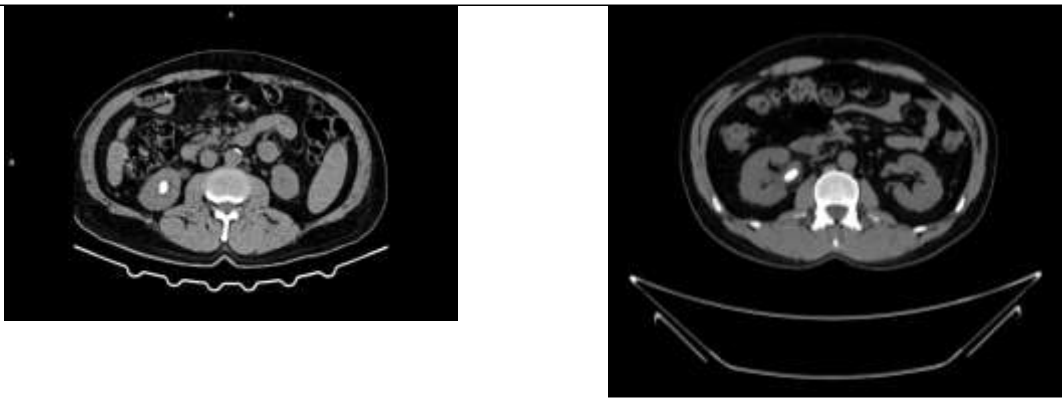

Clinical Dataset Of Kidney Stone CT-Scans | Public Kaggle Dataset Of Kidney Stone CT-Scans

Fig. 2 Dataset *Kidney Stone CT-Scan*

As a comparison, the researchers also collected a public dataset from the Kaggle platform, called Kidney CT-Scan. The Kaggle Kidney CT-Scan dataset consists of CT scan images in JPG and JPEG formats. This dataset totals 2167 images, comprising two public datasets: the first public dataset contains 1377 images, and the second public dataset contains 790 images. Of the total two public datasets from Kaggle, 2135 images were annotated.

Preprocessing Data

The next step is to manually annotate the dataset using Roboflow, a crucial phase in preparing data for machine learning model training. In this research, the objects annotated are kidney stones in CT scan images, involving the identification and marking of each kidney stone to provide consistent labeling across all images in the dataset. Proper annotation allows the machine learning model to be trained to detect and recognize kidney stones in CT scan images with high accuracy, making this process essential for the model's success in object detection.

Fig. 3 Manual Bounding Box Annotation

Segmentation Data

In scientific research and machine learning applications, using a validation dataset obtained through the dataset split process is crucial to ensure model reliability and generalization. Roboflow facilitates the division of data into three main parts: training set, validation set, and test set. The training set forms the basis for training the model to recognize and detect kidney stone features in CT scan images, while the validation set is used to test model performance during training and ensure generalization ability without directly affecting model parameters. The test set evaluates the model's accuracy and effectiveness on new data, ensuring the model's readiness for real-world applications. By separating

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training and validation data, researchers can develop a more accurate and highly valid model, ensuring the developed kidney stone detection model is reliable and has good generalization capabilities.

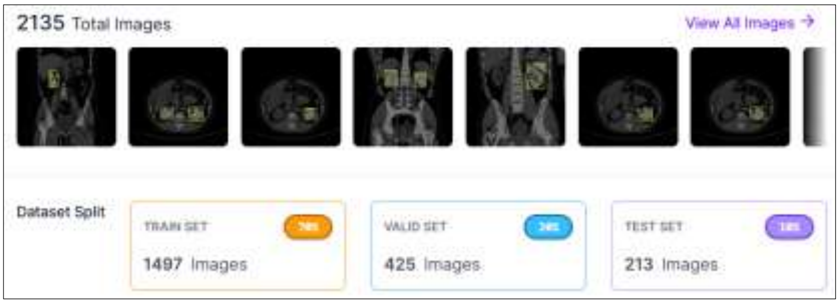

Fig. 4 *Split* Dataset

Model

The YOLOv5 architecture integrates three main components: Backbone, Neck, and Head. The Backbone, consisting of BottleNeckCSP and SPP, is responsible for feature extraction with high efficiency and precision, while the Neck uses Concat, UpSample, Conv1x1, and Conv3x3 to merge and process these features. The Head section, with Conv1x1, is tasked with object detection by converting features into the desired number of classes and calculating bounding boxes. Thus, YOLOv5 is capable of presenting object detection with high speed and accuracy thanks to the solid integration of these three components.

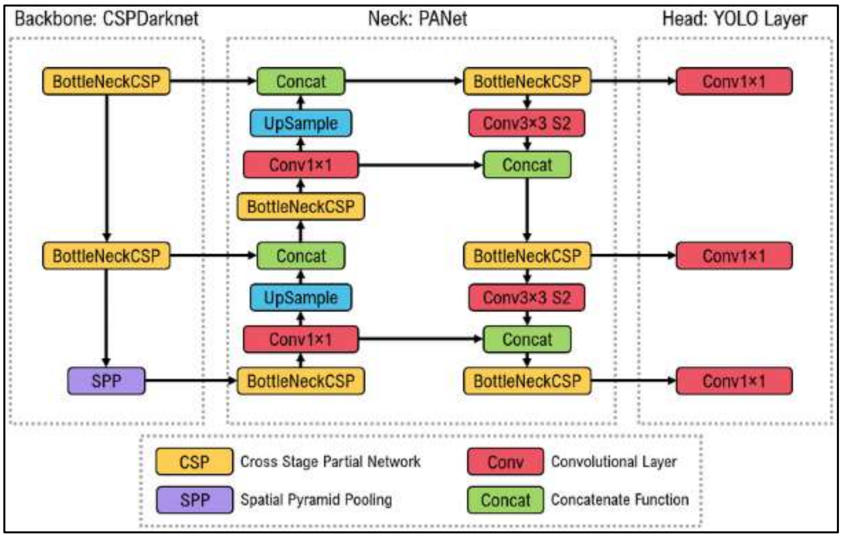

Fig. 5 Architecture of YOLOv5
(Source: The architecture of the YOLOv5 model, which consists of three parts:... |)

YOLOv5 has several model variants: YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x. For devices with limited computational resources such as IoT (Internet of Things) devices, it is recommended to use YOLOv5n because it is the smallest and lightest variant. Meanwhile, for usage in web and mobile applications, it is recommended to use YOLOv5s or YOLOv5m due to their smaller size and higher speed for deployment performance. However, for usage in cloud environments, YOLOv5l or YOLOv5x are more recommended because of their stronger and more accurate detection capabilities.

In this study, we used the YOLOv5m model because it is compatible with deployment in web applications. The choice of YOLOv5m was based on its smaller size and higher speed, allowing for optimal performance when deployed on web applications. Additionally, we did not use YOLOv8 because that model is still unstable and lacks sufficient references. Therefore, YOLOv5m was a more reliable and tested choice for this research needs.

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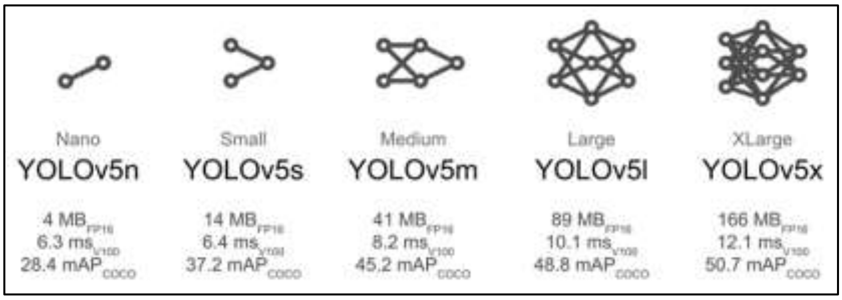

Fig. 6 Type of YOLOv5 Model
(Source: https://api.wandb.ai/files/av-team/images/projects/36872911/9be6fa73.png)

Training YOLOv5 for Object Detection

The dataset exported from Roboflow will be used in the design of the detection model. The following steps in the flowchart diagram help understand the design process. The process begins with creating the dataset in Roboflow. The exported dataset will then be used to train the model by cloning the pre-model YOLOv5 from the official GitHub repository and installing the required packages. Model training is conducted using Google Colab with a Tesla T4 GPU. The dataset from Roboflow is imported, and training is performed by running train.py and filling in the required parameters. Parameters in train.py include img to determine image size (640), batch for batch size (16), epoch for the number of training epochs (150), data for the dataset location, and weights for the location of the model used for transfer learning.

Deployment of the Model and System Design

In implementing YOLOv5 into the deployment architecture, the initial step involves integrating the trained model into the pre-prepared software infrastructure, followed by integration testing to ensure smooth performance within the system. User-friendly interface creation is also conducted to enable users to easily upload kidney CT scan images for analysis. This process is carried out on a VPS server with all necessary dependencies and environments, including Python, Flask, and the trained YOLO model, allowing Flask application access via a domain address for user convenience.

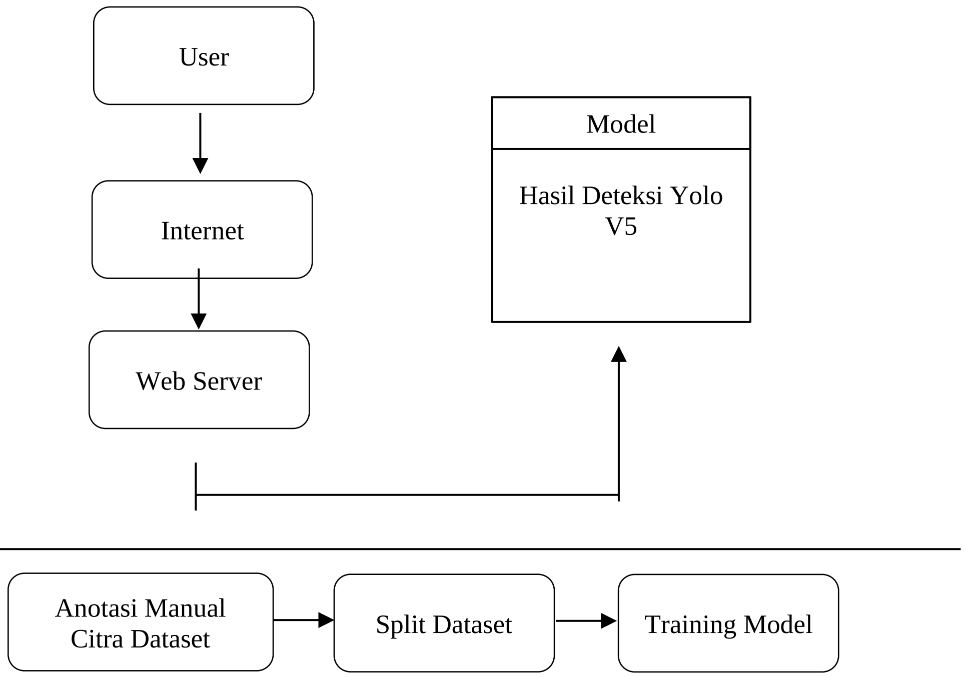

Fig. 7 Architecture of Flask Web Deployment

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In the deployment architecture, the trained model is implemented into a web-based software infrastructure built with Flask. After ensuring smooth integration and installing all required dependencies, including Python and supporting libraries, the Flask application is run on a VPS server. Users can access this detection model via the web by entering the domain address, then uploading kidney stone disease CT scan images, and receiving detection results to determine the presence of kidney stones in the uploaded images.

Model Evaluation

In the clinical testing phase for the clinical dataset, the authors utilized IoU (Intersection over Union) to evaluate the model's performance. IoU is a metric used to measure how well the predicted bounding box by the model overlaps with the actual bounding box. This metric assists in calculating Precision, which is the ratio of correctly predicted objects compared to the total predicted results by the model. Additionally, Recall is also computed, which is the ratio of correctly predicted objects compared to the total number of actual objects. Then, to comprehensively measure performance, the calculation of mean average Precision (mAP) is conducted, which is computed using Precision and Recall values. Precision (P), Recall (R), average Precision (AP), and mean average Precision (mAP) are important metrics used to evaluate and understand the performance of object detection models in the context of clinical testing on clinical datasets.

Intersection over Union is a value based on the statistics of similarity and diversity of sample sets aimed at evaluating the overlapping area between two bounding boxes, namely the predicted bounding box from the model and the original data bounding box. IoU has a minimum value for the predicted result to be considered a true positive, known as the IoU threshold. Below is the IoU equation:

$$IoU = \frac{Area\ of\ Intersection\ of\ two\ boxes}{Area\ of\ Union\ of\ two\ boxes}$$

The IoU threshold is a threshold value of the IoU score of an image successfully detected by the model used to determine whether a bounding box is classified as True Positive or false positive. The IoU threshold value can affect the mAP score. The IoU threshold ranges from 0 to 1. Using a low IoU threshold value can result in a large number of false positives for the model. Conversely, using a higher threshold value can lead to a significant reduction in True Positives during the training process. Adjusting the IoU threshold value appropriately can enhance detection performance. However, if the IoU threshold reduction is too significant, it can lead to a significant reduction in positives.

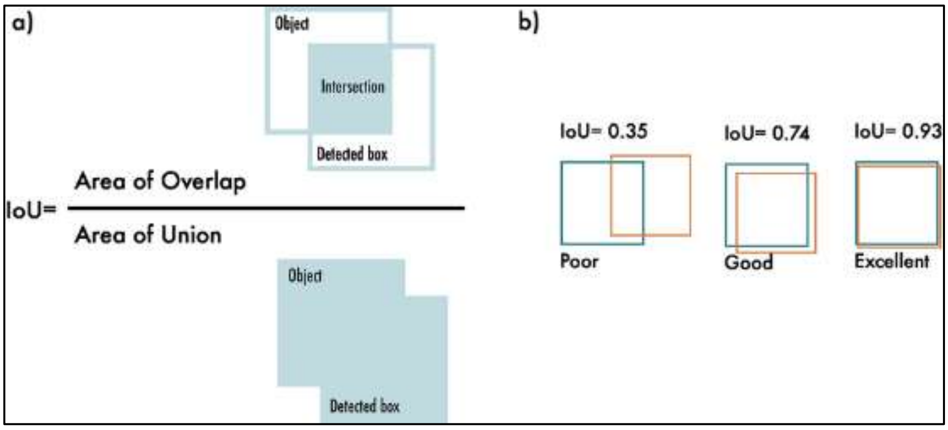

Fig. 8 Illustration and Equation of IoU Threshold
(Source: https://www.researchgate.net/publication/369760111/figure/fig1/)

This stage aims to evaluate the model's performance by measuring Precision, the ratio of correctly predicted objects to the total predicted results by the model, Recall, the ratio of correctly predicted objects to the total actual results, and mean average Precision (mAP) computed using Precision and Recall values. Precision (P), Recall (R), average Precision (AP), and mean average Precision (mAP) need to determine True Positive (TP), which is the number of correctly detected objects, indicating that

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the model successfully recognizes existing objects. False positive (FP) is the number of objects that are not actually present but are incorrectly detected by the model as objects, indicating detection errors. False Negative (FN) is the number of objects that should be present but are not detected by the model, indicating a failure to detect existing objects. True Negative (TN) is the number of areas that truly do not have objects and are not incorrectly detected as objects by the model, indicating that the model does not make detection errors in empty areas. In object detection, an IoU value of 0.5 is used to identify objects in general, while an IoU value of 0.7 is used for more precise object detection (Freund et al., 2021). This study uses an IoU value of 0.7 for model performance evaluation, where the image is considered accurate if the IoU value exceeds 0.7.

RESULT

Evaluation of Public Dataset Model

This testing focuses on kidney stone labels considered as a private dataset. The testing is conducted by recording actual data and comparing it with predicted data. A total of 213 kidney stone datasets from Kaggle were used until the end of the testing. The confusion matrix was obtained as validation from comparing this data, as shown in Table 1. This study used an IoU value of 0.7 as the model performance evaluation. Images are considered accurate if the IoU value exceeds 0.7. In evaluating the model with the public dataset, the number of test data detecting kidney stones from 213 images was used, with the possibility of detecting more than one object in each image.

Table 1. Confusion matrix Kidney Stone Disease

Overall Total			
Total Number Of Data : 267		Predicted Values	
		Negatif	Positif
Actual Values	False	2	8
	True	0	257

Based on the data obtained from the confusion matrix in Table 1, we found that 257 objects were correctly identified as kidney stones (TP), 8 were incorrectly identified as kidney stones (FP), and 2 kidney stones were missed (FN). Additionally, a total of TP + FP (257 + 8 = 265) entries were added to the database. These calculations align with the verification of images sent by the system from the validation database. The data for objects detected with kidney stone disease that should have been sent by the model are TP + TN, totaling 257 images. Therefore, from this test result, we can calculate the accuracy rate, Precision, Recall, and F1-score of the system as follows:

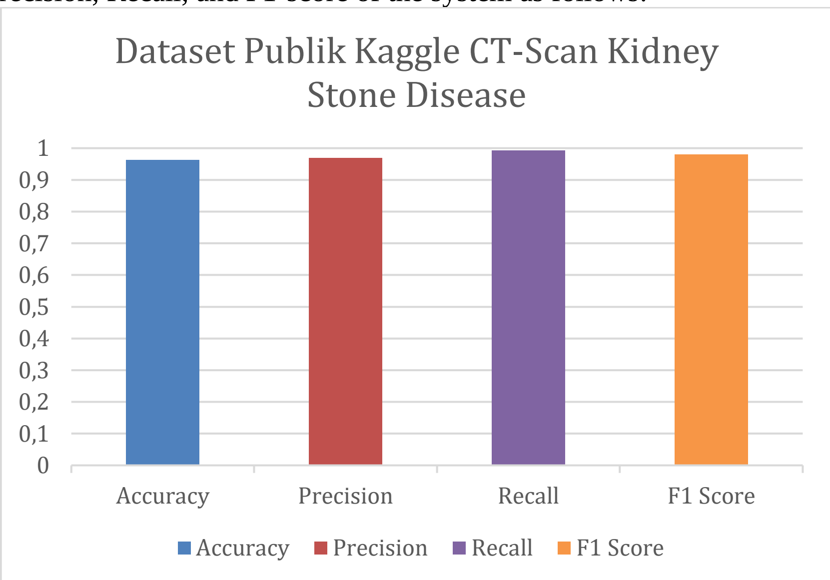

Fig. 9 Kaggle Public Dataset: Kidney Stone CT-Scan

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The accuracy of 96.33% indicates that out of all predictions made by the model, 96.33% of them are correct, although TN is 0 (no negative cases in the dataset), so this accuracy more reflects TP compared to the total predictions. A precision of 96.98% shows that almost all detections made by the model are correct, with only 3.02% being incorrect (False Positives). A recall of 99.23% indicates that the model successfully detects 99.23% of all positive objects in the dataset, with only 0.77% of positive objects being missed (False Negatives). An F1 Score of 98.1% demonstrates a strong balance between high precision and recall, reflecting the model's excellent performance in object detection. The results of this testing show that the system can perform well, with high accuracy and minimal detection errors.

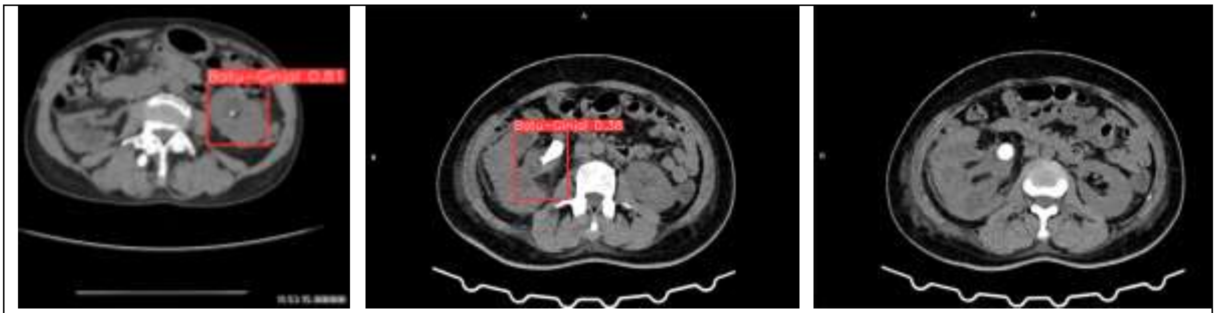
Evaluation of Clinical Dataset Model

This test focuses on kidney stone labels considered as a private dataset, conducted by recording actual data and comparing it with predicted data. A total of 72 images out of 716 clinical (private) dataset were used to evaluate the model. The study used an IoU value of 0.7 as the model performance evaluation, where images are considered accurate if the IoU value exceeds 0.7. The confusion matrix obtained from comparing this data can be seen in Table 2 as follows:

Table 2. Confusion matrix Kidney Stone Disease

Overall Total			
Number of Object Detection Data : 72		Predicted Values	
		Negatif	Positif
Actual Values	False	2	3
	True	0	67

The confusion matrix is employed to evaluate the performance of a YOLO v5 model in detecting kidney stone disease from CT-scan results. True Positive (TP) represents the number of correct detections, where the model accurately identifies kidney stones at their actual locations in the CT images, with an Intersection over Union (IoU) value greater than 0.7. False Positive (FP) indicates incorrect detections, where the model identifies kidney stones in locations where there are none, with an IoU less than 0.7. False Negative (FN) reflects detection failures, where the model fails to identify kidney stones that are actually present in the CT images, potentially due to unreadable detections. By understanding these TP, FP, and FN values, and using an IoU threshold of 0.7, this research evaluates the accuracy and precision of the YOLO v5 model in detecting kidney stone disease from CT-scan results.



True Positif | False Positif | False Negatif

Fig. 10 An example image of kidney stone object detection showing the IoU value

Based on the data obtained from the confusion matrix in Table 2, it was found that 67 images were correctly identified as kidney stones (TP), 3 images were incorrectly identified as kidney stones (FP), and 2 images of kidney stones were missed (FN). Additionally, a total of TP + FP (67 + 3 = 70) entries were added to the database. These calculations align with the verification of images sent by the system from the validation database. The images of kidney stone disease that should have been sent by the model are TP + TN, totaling 67 images. Therefore, from this test result, we can calculate the accuracy rate, Precision, Recall, and F1-score of the system as follows:

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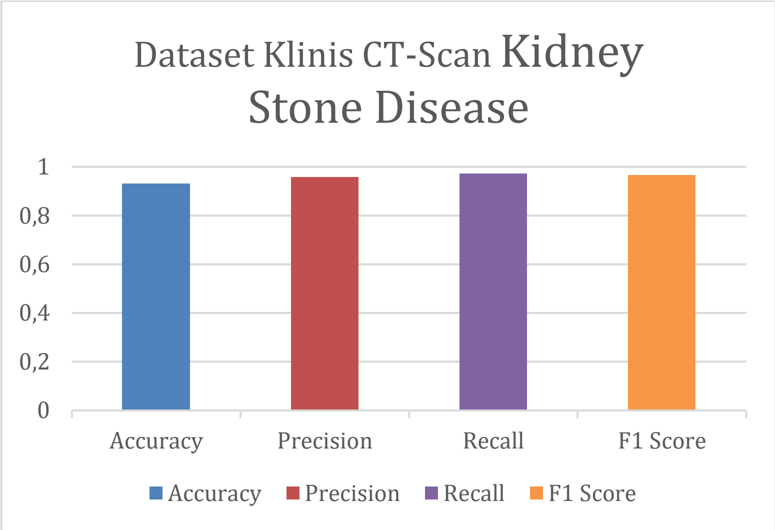

Fig. 11 Dataset Klinis *CT-Scan* Kidney Stone Disease

The accuracy of 93.06% indicates that out of all predictions made by the model, 93.06% of them are correct, although because there are no negative cases in the dataset (TN is 0), this accuracy mainly reflects TP. A precision of 95.71% indicates that 95.71% of positive predictions are indeed correct, with only 4.29% being incorrect (False Positives). A recall of 97.1% means the model successfully detects 97.1% of all positive objects in the dataset, with only 2.9% of positive objects being missed (False Negatives). An F1 Score of 96.49% shows that the model maintains a strong balance between high precision and recall, indicating excellent performance in object detection. The results of this test show that the system can operate effectively, with high accuracy and minimal detection errors.

CONCLUSION

The trained model effectively learns patterns in the training set and demonstrates stable and robust performance on new data. Evaluation results from the public dataset reveal an average mean Average Precision (mAP) of 0.9698 for 'kidney stone' labels. This detection model shows high performance with an accuracy rate of 96.33%, precision of 96.98%, recall of 99.23%, and an F1-score of 98.1%. Clinical data evaluation indicates that the YOLOv5 detection system performs exceptionally well, with an average mAP of 0.9571, accuracy of 93.06%, precision of 95.71%, recall of 97.1%, and F1-score of 96.49%, demonstrating the model's ability to detect kidney stones with high precision and accuracy. The test results indicate that the system has accurate detection capabilities with minimal errors. Based on these findings, it can be concluded that the YOLOv5 deployment system using Flask web technology achieves high accuracy in clinical dataset detection, affirming its accuracy for clinical detection applications.

REFERENCES

Akkasaligar, P. T., & Biradar, S. (2020). Automatic Segmentation and Analysis of Renal Calculi in Medical Ultrasound Images. *Pattern Recognition and Image Analysis*, *30*(4), 748–756. https://doi.org/10.1134/S1054661820040021/METRICS

Aplikasi, P., Pakar, S., Awal, D., Batu, P., Berbasis, G., Dengan, W., & Metode, M. (2022). PERANCANGAN APLIKASI SISTEM PAKAR DOAGNOSA AWAL PENYAKIT BATU GINJAL BERBASIS WEB DENGAN MENGGUNAKAN METODE FORWARD CHAINING. *JURNAL ILMIAH INFORMATIKA*, *10*(01), 15–19. https://doi.org/10.33884/JIF.V10I01.4513

Bagchi, S. (2022). *Digimammocad: a new deep learning-based cad system for mammogram breast cancer diagnosis with mass identification*.

*name of corresponding author

e-ISSN : 2541-2019
p-ISSN : 2541-044X

Bagla, K., Diwan, A. D., & Agarwal, K. (2022). DarthYOLO: Using YOLO for Real-Time Image Segmentation. *Advances in Transdisciplinary Engineering*, *27*, 551–558. https://doi.org/10.3233/ATDE220794

Batubara, Z. H., Hamonangan, Y., Arfan, M., & Hidayatno, A. (2024). Perancangan Sistem Deteksi Pelanggaran Penggunaan Helm Dengan Metode Deep Learning Menggunakan Yolov5 Ultralytic. *Transient: Jurnal Ilmiah Teknik Elektro*, *13*(1), 11–20. https://doi.org/10.14710/transient.v13i1.11-20

Dawami, H., Rachmawati, E., & Sulistiyo, M. D. (2023). Deteksi Penggunaan Masker Wajah Menggunakan YOLOv5. *e-Proceeding of Engineering*, *10*(2), 1746.

Dwiyanto, R., Widodo, D. W., & Kasih, P. (2022). Implementasi Metode You Only Look Once (YOLOv5) Untuk Klasifikasi Kendaraan Pada CCTV Kabupaten Tulungagung. *Seminar Nasional Inovasi Teknologi*, *1*(1), 102–104.

Fan, Y., & Fan, Y. (2023). Image semantic segmentation using deep learning technique. *Applied and Computational Engineering*, *ACE Vol.4*(1), 810–817. https://doi.org/10.54254/2755-2721/4/2023439

Ferraro, P. M., Robertson, W., & Unwin, R. (2023). Renal stone disease. *Medicine (United Kingdom)*, *51*(4), 229–233. https://doi.org/10.1016/j.mpmed.2023.01.007

Freund, T., Hamdaoui, Y., & Spiwack, A. (2021). Union and intersection contracts are hard, actually. In *DLS 2021 - Proceedings of the 17th ACM SIGPLAN International Symposium on Dynamic Languages, co-located with SPLASH 2021* (Vol. 1, Nomor 1). Association forComputing Machinery. https://doi.org/10.1145/3486602.3486767

Gothane, D. S. (2021). A Practice for Object Detection Using YOLO Algorithm. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 268–272. https://doi.org/10.32628/cseit217249

Hatami, M., Tukino, T., Nurapriani, F., Widiyawati, W., & Andriani, W. (2023). *View of DETEKSI HELMET DAN VEST KESELAMATAN SECARA REALTIME MENGGUNAKAN METODE YOLO BERBASIS WEB FLASK*. https://journalstkippgrisitubondo.a.id/index.php/EDUSAINTEK/article/view/651/429

Hoffman, A. (2021). *Kidney Disease: Kidney Stones*. https://typeset.io/papers/kidney-disease-kidney-stones-4xd320h69e

Howles, S. A., & Thakker, R. V. (2020). Genetics of kidney stone disease. *Nature Reviews Urology 2020 17:7*, *17*(7), 407–421. https://doi.org/10.1038/s41585-020-0332-x

Indaryanto, F., Nugroho, A., & Alfa Faridh Suni, D. (2021). Aplikasi Penghitung Jarak dan Jumlah Orang Berbasis YOLO Sebagai Protokol Kesehatan Covid-19. *Edu Komputika Journal*, *8*(1), 31–38. https://doi.org/10.15294/EDUKOMPUTIKA.V8I1.47837

Jha, V., RajendraPrasad, M., & Jain, S. (2022). Covid 19 Prediction Through Chest CT Scans using Deep Learning and Deploying Model on Flask Web. *Proceedings - 2022 2nd International Conference on Innovative Sustainable Computational Technologies, CISCT 2022*. https://doi.org/10.1109/CISCT55310.2022.10046647

Kavitha, A. R., & Palaniappan, K. (2023). Brain tumor segmentation using a deep Shuffled-YOLO

*name of corresponding author

network. *International Journal of Imaging Systems and Technology*, *33*(2), 511–522. https://doi.org/10.1002/IMA.22832

Lemay, A. (2019). *KIDNEY RECOGNITION IN CT USING YOLOV3 A PREPRINT*. https://www.theobjects.com/dragonfly/

Minaee, S., Boykov, Y., Porikli, F., Plaza, A., Kehtarnavaz, N., & Terzopoulos, D. (2022). Image Segmentation Using Deep Learning: A Survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *44*(7), 3523–3542. https://doi.org/10.1109/TPAMI.2021.3059968

Muhd Suberi, A. A. (2020). *An improved diagnostic algorithm based on deep learning for ischemic stroke detection in posterior fossa*.

Nugraha, K. C., & Sipayung, E. M. (2023). VEHICLE LICENSE PLATE DETECTION USING YOLO ALGORITHM. *Jurnal Algoritma, Logika dan Komputasi*, *6*(2), 605–611. https://doi.org/10.30813/J-ALU.V6I2.4739

Pattanayak, S. (2023). Introduction to Deep-Learning Concepts and TensorFlow. *Pro Deep Learning with TensorFlow 2.0*, 109–197. https://doi.org/10.1007/978-1-4842-8931-0_2

Pranovich, A. A., Ismailov, A. K., Karelskaya, N. A., Kostin, A. A., Karmazanovsky, G. G., & Gritskevich, A. A. (2022). Artificial intelligence in the diagnosis and treatment of kidney stone disease. *Russian Journal of Telemedicine and E-Health*, *8*(1), 42–57. https://doi.org/10.29188/2712-9217-2022-8-1-42-57

Pulipalupula, M., Patlola, S., Nayaki, M., Yadlapati, M., Das, J., & Sanjeeva Reddy, B. R. (2023). Object Detection using You only Look Once (YOLO) Algorithm in Convolution Neural Network (CNN). *2023 IEEE 8th International Conference for Convergence in Technology, I2CT 2023*. https://doi.org/10.1109/I2CT57861.2023.10126213

Rathod, J., & Trivedi, K. (2021). CUSTOM OBJECT DETECTION, TRACKING AND WEB API WITH YOLO AND FLASK USING DARKNET NEURAL NETWORK FRAMEWORK. *International Research Journal of Engineering and Technology*. www.irjet.net

Relan, K. (2019). Beginning with Flask. *Building REST APIs with Flask*, 1–26. https://doi.org/10.1007/978-1-4842-5022-8_1

Vysakh V Mohan, Pradeep Prakash, & Resmi K R. (2022). A Survey on Deep Learning Concepts and Techniques. *International Journal of Advanced Research in Science, Communication and Technology*, 20–27. https://doi.org/10.48175/IJARSCT-4903

Wibowo, A., Lusiana, L., & Dewi, T. K. (2023). Implementasi Algoritma Deep Learning You Only Look Once (YOLOv5) Untuk Deteksi Buah Segar Dan Busuk. *Paspalum: Jurnal Ilmiah Pertanian*, *11*(1), 123. https://doi.org/10.35138/paspalum.v11i1.489

Yudha Sambawitasia, I. P., Irma Wulandari, P., & Sukadana, K. (2022). Pemeriksaan Ct Stonografi Pada Kasus Nefrolithiasis. *JRI (Jurnal Radiografer Indonesia)*, *5*(2), 96–103. https://doi.org/10.55451/jri.v5i2.133

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