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Enhancing Practical AI Competency with YOLO 2D Detector Object Localization Technology

Nova Eka Budiyanta *[1], Hanugra Aulia Sidharta [2], Stefani Prima Dias Kristiana [3], Diah Risqiwati[4]

[1]Dept. of Electrical Engineering, School of Bioscience Technology and Innovation, Universitas Katolik Indonesia Atma Jaya, Jl. Raya Cisauk Lapan, Sampora, Cisauk, Tangerang, Banten, Indonesia 15345

[2]Computer Science Departement, School of Computer Science, Bina Nusantara University, Jl. Raya Kb. Jeruk No.27, RT.1/RW.9, Kemanggisan, Kec. Palmerah, Kota Jakarta Barat, DKI Jakarta, Indonesia 11530

[3]Dept. of Industrial Engineering, School of Bioscience Technology and Innovation, Universitas Katolik Indonesia Atma Jaya, Jl. Raya Cisauk Lapan, Sampora, Cisauk, Tangerang, Banten, Indonesia 15345

[4]Departement of Informatics, Universitas Muhammadiyah Malang, Jl. Raya Tlogomas No.246, Babatan, Tegalgondo, Kec. Lowokwaru, Kota Malang, Jawa Timur, Indonesia 65144

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Abstract

Object locatization is one of important aspect of computer vision, which refers to a system's ability to detect and determine the position of objects within an image. However, general audience practical understanding of object localization is remains limited. To address this issue as a community service team, and organized a workshop focused on YOLO (You Only Look Once)-based object localization. This workshop was conducted free of charge online via the Google Colab platform. The event was successfully carried out and received positive feedback from the participants. This workshop are providing a real studycase through brain tumor detection from image-based approaches, aiming to provide an in-depth experience in object localization while also offering the latest updates on artificial intellegent technology trends based on digital image processing. Based on evaluation results indicated that the majority of participants, who previously had no experience in object detection, were able to understand the fundamental concepts of object localization and apply them directly using the cloud platform. This workshop demonstrates that cloud-based learning approaches utilizing Google Colab and Roboflow are highly effective in bridging the gap between theory and practice in object localization.

1. INTRODUCTION

Artificial intelligence (AI) within the domain of computer vision has grown to become a fundamental pillar across various fields in the current era, spanning from manufacturing industries and surveillance systems to the medical sector (Szeliski, 2022). One of the key applications in computer vision is object localization, which refers to a system's ability to detect and determine the position of objects within an image. However, practical understanding of object localization remains limited among the general audience, particularly those without a technical background.

To bridge this gap, we organized an open workshop focused on YOLO (You Only Look Once)-based object localization. This workshop was free and accessible via the Google

*Corresponding author. Nova Eka Budiyanta
Email address: nova.eka@atmajaya.ac.id

Colab platform. The initiative aimed to introduce image processing methods for object localization using an accessible and hands-on approach. Additionally, the workshop sought to indirectly encourage participants to grasp the fundamentals of AI implementation and deep learning technologies in real-world contexts (Chollet, 2021; Redmon & Farhadi, 2018).

YOLO is a state-of-the-art, single-stage object detection algorithm that predicts bounding boxes and class probabilities directly from full images in one evaluation, enabling real-time detection with high speed and accuracy (Redmon *et al*., 2016). Its architecture has evolved through several versions, improving detection accuracy and efficiency, and has been widely adopted in domains such as autonomous driving, medical imaging, and surveillance (Bochkovskiy *et al*., 2020; Li *et al*., 2023).

Through online platforms such as Google Colab, this workshop offers significant opportunities for practice-based learning by enabling users to run Python code and machine learning models without the difficulties of local installations and library dependencies, requiring only an internet connection (Bisong, 2019). This approach has proven highly effective in AI education by removing technical barriers that often hinder beginners (Géron, 2019). Furthermore, the application of YOLO as a real-time object detection model has been widely adopted in both research projects and industrial applications due to its efficiency in speed and accuracy (Bochkovskiy *et al*., 2020; Budiyanta *et al*., 2022; Diwan *et al*., 2023; Zong *et al*., 2023).

2. METHOD AND IMPLEMENTATION

The workshop was conducted online with a duration of five hours, targeting participants from diverse technical backgrounds. To facilitate understanding, the workshop materials were provided through Google Colab as an online platform, enabling participants to replicate the approach across various case studies involving object localization through image processing. To assess the effectiveness of the workshop, an evaluation was conducted using a questionnaire. Participants' personal data were anonymized to preserve the objectivity of the responses. The workshop was structured into four sessions, detailed as follows.

a. Introduction

In this session, participants were introduced to the advancements in digital image processing technology and provided with a detailed explanation of the differences between image classification, object localization, and object detection. This explanation is essential for participants to gain a fundamental and conceptual understanding of digital image processing. The discussion was presented in detail from the perspectives of objectives, outputs, and technical complexity. Image classification aims to categorize the entire content of an image into one or more labels without considering the position of objects within it. While object localization not only identifies the type of object but also determines the precise location of specific objects through bounding boxes. In contrast, object detection involves a higher level of complexity compared to the previous methods, as it must detect, classify, and localize multiple objects simultaneously within a single image. The output of object detection includes multiple bounding boxes along with class labels and confidence scores for each detected object. However, this approach requires greater computational resources and representation capacity than the other two methods due to its increased flexibility and complexity. Therefore, understanding these three concepts is considered crucial as a foundation before guiding participants to directly implement the YOLO object detector in object localization tasks

b. Theoritical coding

In this session, participants were guided to implement YOLOv8 on the Google Colab platform. The practical session consisted of two stages. In the first stage, participants were guided to implement YOLOv8 using pretrained weights and tested on object detection in images with object classes corresponding to the COCO dataset. Subsequently, participants were also guided to use YOLOv8 to perform real-time object detection directly from webcam streaming. In the second stage, participants were guided to create their own training dataset based on brain MRI images indicating the presence of tumors. They were instructed on how to annotate tumor locations and create the training dataset using the Roboflow platform. Following this, participants used the dataset created with Roboflow to train the YOLO model on Google Colab. By the end of the session, participants successfully demonstrated tumor object localization results in the form of bounding boxes on test images.

c. Study case exploration.

After completing the basic training, participants were encouraged to further explore by modifying the source code, such as adjusting the confidence parameter to control the number of bounding boxes generated based on confidence values, and customizing the training data input. The objective of this session was to foster participants' applied understanding and problem-solving skills in addressing object localization cases.

d. Summary

At the end of the workshop, participants were asked to complete an anonymous satisfaction survey. Aimed to providing feedback on the content, delivery, and practical experience. Additionally, a verbal disccusion session was conducted to review what had been learned and discuss its real-world applications, particularly in the medical field.

To facilitate easy access for participants, this workshop utilized cloud-based platforms, eliminating the need for specialized hardware or complex library configurations. The platforms used in this activity include:

a. Google Colab

Google Colab served as the primary Integrated Development Environment (IDE) for writing and executing Python code. Being cloud-based, it enables participants to run deep learning models without requiring high-end hardware specifications. Participants only need a stable internet connection and a web browser to access Google Colab.

b. Ultralytics YOLOv8

The workshop employed YOLOv8 as the main model for object localization. This model is well-known for its fast and accurate inference capabilities, supported by extensive documentation and a large community. In this workshop, YOLOv8 was used to detect and draw bounding boxes on brain MRI images containing tumors.

c. Roboflow

Roboflow was used to manage datasets, annotate bounding boxes on tumor objects in brain MRI images, and facilitate exporting datasets in formats compatible with YOLO models. This platform simplifies data preprocessing and integration into the Google Colab pipeline. Additionally, Roboflow allows participants to visualize and structure the data labeling workflow effectively.

d. Online Questionnaire through Google Form

The workshop evaluation was conducted using an online survey designed with a Likert scale to measure participants' perceptions of the content, delivery, and practical experience. The survey responses were collected anonymously to protect participant privacy.

3. RESULT AND DISCUSSION

The YOLOv8-based object localization workshop, featuring a brain tumor detection case study, was successfully conducted online. Participants engaged in the entire workshop series, beginning with an introduction to the concepts and followed by hands-on implementation on Google Colab individually. Participants were also encouraged to independently explore datasets using Roboflow. The training materials covered fundamental theories of digital image processing, preprocessing technique, model configuration, and object detection using YOLO annotation formats. To evaluate the resulting models, participants were equipped with basic techniques to assess bounding box prediction outcomes based on confidence scores. Participants were introduced to the visual annotation process of brain tumor datasets via Roboflow and practiced creating, downloading, training, and testing the dataset using the YOLOv8 model on Google Colab. The workshop was conducted in four stages. In the first stage, participants attended a presentation on image interpretation, which included distinctions among image classification, object localization, and object detection. The summary of this session is presented in Table 1.

Table 1.
Comparison of Image Classification, Object Localization, and Object Detection in Computer Vision Tasks

Aspect	Image Classification	Object Localization	Object Detection
Goal	Classifies the entire image.	Identifies and localizes one object.	Identifies and localizes multiple objects.
Output	One or multiple labels.	Single bounding box + label.	Bounding boxes + labels + confidence scores.
Focus	What is in the image.	What and where is a specific object.	What and where are the objects.
Number of Objects	Usually one label per image.	One object of interest.	Multi-label for multiple objects.
Need for Location	Ignores object position.	Identifies position of one object.	Identifies positions of all objects.
Complexity	Simpler.	Medium complexity.	Most complex, requires bounding boxes.

To facilitate readers' understanding, the summary of the material covered in this session is also presented visually and can be seen in Figure 1.

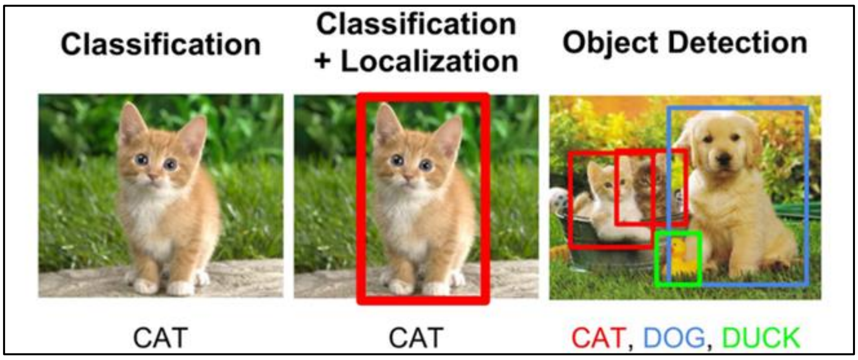

Figure 1.
Example of three type of image classification

In the second stage, participants ran inference scripts on common objects belonging to one of the label categories from the COCO dataset. The pretrained weight yolov8n.pt was used in this inference system. The data before and after detection are shown in Figure 2. The inference system was then extended from static images to video streaming using a webcam, providing participants with insight into how a trained YOLO model can be used for real-time inference based on streaming image data from a camera.

(a) (b)

Figure 2.
The illustration of object detection in the case of road transportation, with (a) as the original image and Figure (b) with the addition of object detection.

The third stage involved exploration, where participants were invited to create a training dataset from available medical images using Roboflow, and subsequently train a YOLO model with the created dataset. The image annotation process using Roboflow is illustrated in Figure 3. After successfully training the model, participants performed inference using their trained models to test new images outside the training set and modified inference parameters to achieve optimal results. The effects of parameter modifications are shown in Figure 4.

Figure 3.
Exploring MRI data by manually anotate on specific disease

Finally, the fourth stage served as the closing activity, including a review of the entire workshop process and participants completing an evaluation survey to provide feedback on their experience. Throughout the workshop, participants were encouraged to understand not only "what" object was classified but also "where" the object, specifically, brain tumors in MRI images, was located. Participants successfully replicated the material and applied it using their own Roboflow and Google Colab accounts, achieving accurate object localization results with the same model. This outcome demonstrates the successful knowledge transfer facilitated by the workshop.

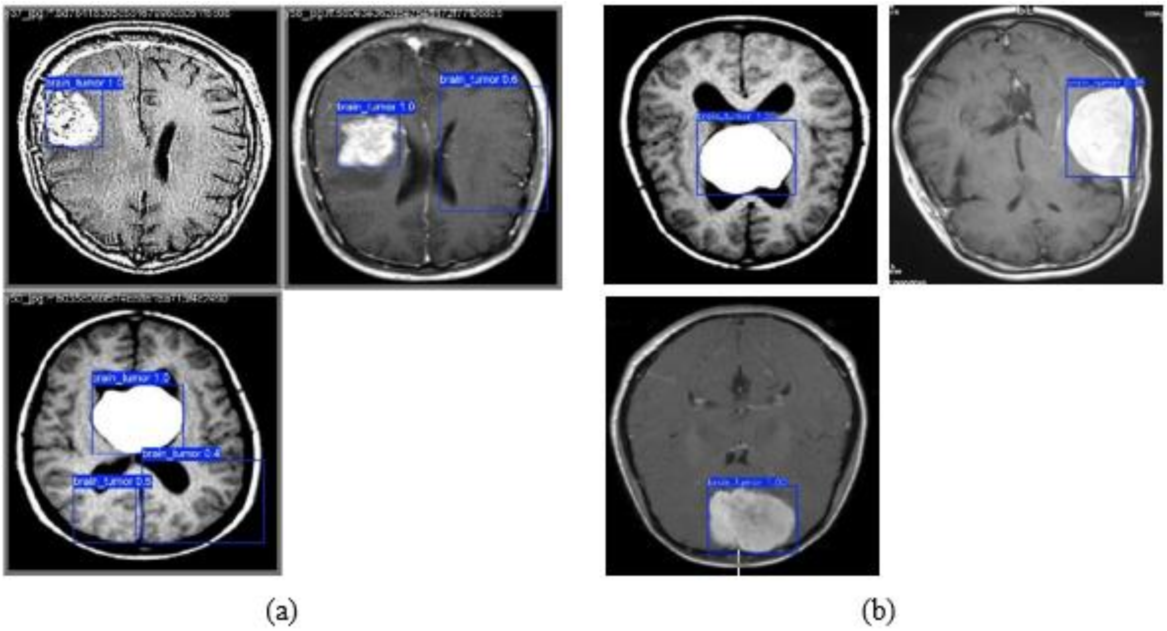

Figure 4.
Effect of Varying the Confidence Score Threshold on IoU Results: (a) When the confidence score threshold is set to 0.4, all bounding boxes with a confidence score above 0.4 are displayed; (b) When the threshold is increased to 0.8, only bounding boxes with a confidence score above 0.8 are shown.

The workshop was attended by 41 participants, comprising both males and females aged between 20 and 40 years. Participants completed a survey that began by exploring their prior experience with using YOLO for object detection purposes. Based on the pre-workshop data collected, it can be concluded that the majority of participants had no prior experience in object detection using YOLO. Specifically, 73.2% of respondents indicated "Never Used," demonstrating that most participants were beginners in this topic. Meanwhile, 24.4% of participants reported having "Heard About It," suggesting some theoretical exposure without hands-on practice. In contrast, only 2.4% of participants had previous practical experience with YOLO. The distribution of participants' experience levels is illustrated in Figure 5.

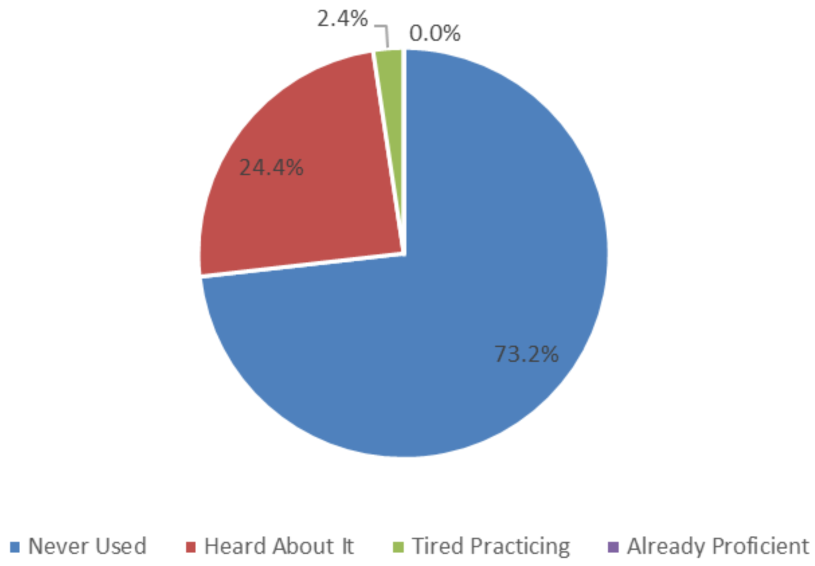

Figure 5.
Previous Experience in Object Detection using YOLO

This distribution indicates that the workshop successfully reached its intended target audience, individuals who require foundational literacy and hands-on experience with object localization technology within the context of practical AI. The workshop served as a crucial initial step in introducing the concepts, tools, and real-world applications of YOLO, particularly in medical imaging applications such as brain tumor localization.

The survey continued with a questionnaire consisting of 10 statements assessed using a 4-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Agree, 4 = Strongly Agree). The results of the questionnaire analysis are presented in Table 2

Table 2.
Average Scores of Participant Feedback on the Object Localization Workshop

No.	Rated aspect	Average score
1	Workshop materials are easy to understand.	2.905
2	The delivery of materials is clear and structured.	3.238
3	Explanation of the concept of object localization helps understanding.	2.929
4	Google Colab practice runs smoothly.	2.786
5	Implementation steps are easy to follow.	2.667
6	Tumor case examples are relevant and interesting.	3.190
7	Facilitator assistance is sufficient during practice.	3.119
8	Time provided is sufficient	2.905
9	Workshop improves understanding of object localization	3.143
10	Workshop encourages participants to explore further in the field of AI	3.143
Total score		**3.002**

Based on the evaluation of the 10 aspects presented in Table 2, it can be concluded that the highest-rated aspect was the clarity and structure of the material delivery, with a score of 3.238. This indicates that the approach to presenting the material was effective for the participants. However, the aspects of "Ease of following implementation steps" and

"Smooth operation of Google Colab practice" received lower scores of 2.667 and 2.786, respectively, suggesting that technical challenges or the need for more detailed guidance during hands-on practice still exist. Overall, the average score across all aspects was 3.002, indicating a good level of participant satisfaction with the workshop.

On the other hand, the relevance of the brain tumor case study received a high score of 3.190, and the encouragement for further exploration also scored highly at 3.143, demonstrating the workshop's success in fostering interest and connections within the medical context. The workshop activities are documented in Figure 6.

Figure 6.
Documentation of the Object Localization Workshop

The evaluation results indicate that the workshop had a positive impact across several areas, both in terms of participants' understanding of the technology and their motivation to pursue further exploration in AI. The findings show that the majority of participants, who previously had no experience in object detection, were able to grasp the fundamental concepts of object localization and apply them directly using cloud-based platforms.

Several tangible impacts identified from this activity include an increase in AI technology literacy, as participants were able to identify, understand, and independently practice object localization processes using the YOLO model. Additionally, there was a transfer of digital skills, with the use of tools such as Roboflow and Google Colab introducing participants to an AI development ecosystem relevant to both industry and research. Furthermore, there was a notable increase in interest for further exploration, with 78% of participants agreeing or strongly agreeing that the workshop motivated them to study AI more deeply, particularly in the context of medical applications. Moreover, the MRI brain image-based case study approach successfully bridged the gap between AI theory and its application in a socially impactful and contextual domain.

Despite these promising outcomes, the workshop had several limitations that provide opportunities for future improvement. The scope of the material was limited to a single case study involving brain tumor localization, which may not fully represent the diverse applications of object localization across different field such as agriculture, transportation, or industrial inspection. The participant's varying levels of technical skills also led to disparities in engagement, especially in a fully online format that restricted real-time and persinalized assistance from facilitators. In addition, the impact evaluation relied solely on self reported perceptions, without objective measures to assess actual skill acquisition. To address these limitations and build upon the current success, the organizing team plans to develop follow up modules covering a broader range of object localization applications, provide structured open access learning materials, and establish an online mentoring forum to support independent exploration.

4. CONCLUSION

The workshop titled "Enhancing Practical AI Competency with YOLO 2D Detector Object Localization Technology" was successfully conducted and received positive feedback from participants. Focusing on the case study of brain tumor detection, this initiative provided a contextual and meaningful experience while introducing AI technology based on computer vision to participants, most of whom had no prior experience. The workshop demonstrated that a cloud-based learning approach using Google Colab and Roboflow is highly effective in bridging the gap between theory and practice in object localization. Evaluation results indicated high satisfaction scores in aspects such as content delivery, case relevance, and increased motivation for further exploration.

With its open design, free platform, and contextual materials, this activity holds great potential to be replicated as a form of community service across interdisciplinary communities and professional groups interested in AI. This workshop model can serve as an inclusive, adaptive, and impactful approach to practical AI literacy. It is expected to act as a catalyst for the development of similar training programs that bridge advanced technology with real societal needs, as well as strengthen the integration of teaching, research, and community service within a sustainable learning ecosystem.

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