Security of Infocommunication Systems and Internet of Things

2025 Vol 3, No 2

https://doi.org/10.31861/sisiot2025.2.02002

Received 13 June 2025; revised 03 November 2025; accepted 13 November 2025; published 30 December 2025

Preprocessing of Object Images Before Their Detection Using YOLO Neural Network

Serhiy Balovsyak[1,*] and Serhii Stets[2]

[1]Department of the Computer Systems and Networks, Yuriy Fedkovych Chernivtsi National University, Chernivtsi, Ukraine
[2]Department of Computer Systems Software, Yuriy Fedkovych Chernivtsi National University, Chernivtsi, Ukraine

*Corresponding author (E-mail: s.balovsyak@chnu.edu.ua)

ABSTRACT Software was developed in Python for the digital processing of object images before their detection using the You Only Look Once (YOLO) artificial neural network. Detection was carried out on object images, specifically vehicles and other road users. The preprocessing of images was performed through histogram equalization and local contrast enhancement. The original images were read from video cameras or graphic files. Image detection was performed using the medium-sized YOLO convolutional neural network model, YOLOv8m. As a result of detection, the studied objects, particularly cars, were highlighted with rectangular bounding boxes. To evaluate the accuracy of object detection, several metrics (parameters) were used: Precision, Recall, Intersection over Union (IoU), F1, and Average Precision (AP). The YOLO network was pre-trained on the Common Objects in Context dataset. The YOLO neural network returns the object recognition confidence, the coordinates of its center (x, y) on the image, and its width and height (w, h). The detected objects are marked with rectangular bounding boxes. The positioning of objects in the images was manually performed using the Roboflow tool, which allows for accurate spatial positioning of each object. The study of the impact of image preprocessing on the accuracy of object detection by the YOLO network was conducted using a typical traffic scene image. After histogram equalization, the histogram becomes more symmetrical and uniform, improving the visual quality of both dark and bright areas. This led to improved object detection accuracy across almost all metrics. The increase in detection accuracy by the IoU parameter is 0.169. The summary improvement in detection accuracy by the IoU, F1, AP parameters is 0.502. It was shown that after image preprocessing, detection accuracy increased, and all vehicles were correctly detected. The developed software can be used in various computer vision systems as well as in Internet of Things systems for remote monitoring and control.

KEYWORDS digital image processing, artificial neural networks, YOLO, object detection, software.

I. INTRODUCTION

Object detection in images has significant practical importance in the development of modern computer vision systems [1-5]. In particular, the detection of vehicle images [6, 7] is used for automated and automatic remote monitoring and control of road traffic conditions in various Internet of Things (IoT) systems [8]. One of the most effective tools for object image detection is convolutional neural networks with the You Only Look Once (YOLO) architecture, which are characterized by high accuracy and speed [9]. The high performance of YOLO is explained by the fact that objects are detected in a single pass. YOLO's high object localization accuracy is achieved through improved feature detection mechanisms. The YOLO network enables object detection not only in individual images but also in real-time video streams.

However, in some cases, the spatial localization accuracy of objects using YOLO networks is insufficient.

The potential for improving vehicle detection accuracy with a modified YOLOv5 network is discussed in [10]. Due to network modifications, the likelihood of false detections – especially for small objects or overlapping objects – was reduced. However, YOLOv5 is not a recent version, making it advisable to use more modern YOLO versions (e.g., v8).

The capabilities of YOLOv8 for detecting vehicle images are discussed in [11]. The study showed limited YOLO accuracy in detecting car images under complex traffic conditions, especially for small, overlapping, or shadowed vehicles.

Research in [12] showed that the accuracy of YOLOv8 in vehicle detection can be improved through fine-tuning of the network. However, fine-tuning a neural network requires a specialized dataset and extended training time. The analysis of the reviewed studies demonstrated the promise of using YOLOv8 and the need to improve its accuracy.

The challenge lies in the fact that when processing images with low contrast or extremely high or low brightness, detection accuracy significantly decreases. It is particularly difficult to detect objects in images that simultaneously contain local areas with low, medium, and high brightness. Such image conditions arise due to lighting and weather conditions, which are difficult or impossible to control.

Therefore, the research aim is to increase the accuracy of object detection by preprocessing of digital image through histogram equalization and local contrast enhancement [13-16]. Software-based preprocessing is much simpler to implement than neural network retraining. The system supports reading input images from either video cameras or graphic files [17].

II. METRICS FOR EVALUATING OBJECT DETECTION ACCURACY

To evaluate the accuracy of object detection, a number of metrics (parameters) are used: Precision, Recall, Intersection over Union (IoU), Average Precision (AP), and F1 (a combined measure of Precision and Recall) [2, 18]. The Recall metric is calculated as the ratio of the number of correctly detected objects True Positives (TP) to the total number of actual objects in the image, using the formula:

$$Recall = \frac{TP}{TP + FN}, \tag{1}$$

where False Negatives (FN) is the number of real objects that were not detected.

The higher the Recall value, the greater the percentage of actual objects that have been detected. High recall is especially important in scenarios where it is critical to detect all relevant objects in the image.

The Precision metric is defined as the ratio of correctly detected objects TP to the total number of detected objects in the image:

$$Precission = \frac{TP}{TP + FP}, \tag{2}$$

where False Positives (FP) is the number of falsely detected objects that are actually not present in the image.

A high Precision value indicates that most detected objects are correct.

Precision and Recall describe different aspects of the detection process. To combine them, the F1 score is used, which is calculated as:

$$F1 = 2\frac{Precision \cdot Recall}{Precision + Recal}. \tag{3}$$

The spatial localization accuracy of an object in an image is described by the IoU metric, which is defined as the ratio of the area of overlap between the predicted and the actual (ground truth) bounding boxes to the area of their union:

$$IoU = \frac{|A \cap B|}{|A \cup B|}, \tag{4}$$

where $|A \cap B|$ – area of intersection of the two boxes, $|A \cup B|$ – area of their union.

The AP metric is calculated as the average value of detection precision for a single object class at a fixed IoU threshold of 0.5. It is defined by the formula:

$$AP = \int_0^1 P(R)dR, \tag{5}$$

where $P(R)$ represents the value of Precision as a function of Recall.

Based on the described metrics, more complex ones can be derived, such as Mean Average Precision at IoU = 0.5 (mAP50), which is the average of AP values across all object classes.

III. SOFTWARE FOR PREPROCESSING AND OBJECT DETECTION

The software implementation of the system for preprocessing and detecting object images was developed in Python on the cloud platform Google Colab (in a Jupyter Notebook). Color digital images were programmatically processed as arrays $I_C(i, k, c)$, where $i = 0,..., M$-1; $k = 0,..., N$-1; $c = 0,..., K$-1; M is image height (in pixels), N is image width, $K = 3$ – quantity of color channels. Object detection in images was performed using the YOLOv8 network version (medium-sized model YOLOv8m) [9], pre-trained on the Common Objects in Context (COCO) dataset. The YOLOv8 neural network returns the confidence of object recognition, coordinates of its center (x, y) on the image, and width and height (w, h). Detected objects are highlighted with rectangular bounding boxes.

The positioning of objects (e.g., vehicles) in the images was carried out manually using the Roboflow tool [19], which allows precise spatial positioning of each object (image annotation). The coordinates of the correct bounding boxes, set in Roboflow, are saved in a specific format and read by the Python program. During programmatic object detection, the bounding boxes predicted by YOLO are compared to the correct ones, which allows for an objective evaluation of detection accuracy.

Histogram equalization of images through automatic brightness level adjustment was performed using a Python program (with the "equalizeHist" function) or the graphic editor Paint.NET. Local contrast enhancement was performed using a Python program (via the CLAHE method). To ensure high visual image quality [20], noise filtering [21] was applied when necessary using Gaussian or impulse filters [13].

IV. EXAMPLES OF OBJECT DETECTION IN IMAGES

A study of the impact of object image preprocessing on the accuracy of their detection by the YOLO network was carried out using a typical road traffic image (Fig. 1) [22].

In the image under study, the correct rectangular regions of vehicles # 1-3 were annotated using the Roboflow service (green boxes) (Fig. 2). As a result of detection, the predicted regions of vehicles # 4-6 are highlighted (red boxes).

FIG. 1. Original road traffic image.

FIG. 2. Vehicle detection on the original image.

Without preprocessing, detection accuracy proved to be low (Fig. 2). In particular, in region # 1, the reflection of a vehicle in the window glass is detected as two separate vehicles (# 4 and # 5), while vehicle # 2 is not detected at all.

After histogram equalization of the image, detection accuracy improved (Fig. 3), and all vehicles are correctly detected, including vehicle # 2, which has small dimensions. Similar results were obtained when enhancing the local contrast of the images.

For brightness values z of the studied images, their histograms $h(z)$ were calculated (Fig. 4). A series of image studies showed that the greatest improvement in detection accuracy was achieved through histogram equalization when processing images with an asymmetric brightness histogram (Fig. 4a), i.e., dominated by either dark or light regions (Fig. 1). After histogram equalization, the histogram becomes more symmetrical and uniform (Fig. 4b), which improves the visual quality of both dark and light regions. As a result, detection accuracy of objects improved across nearly all metrics (parameters). The increase in detection accuracy by the IoU parameter is 0.169. The summary improvement in detection accuracy by the IoU, F1, AP parameters is $s_d = 0.502$ (Fig. 5).

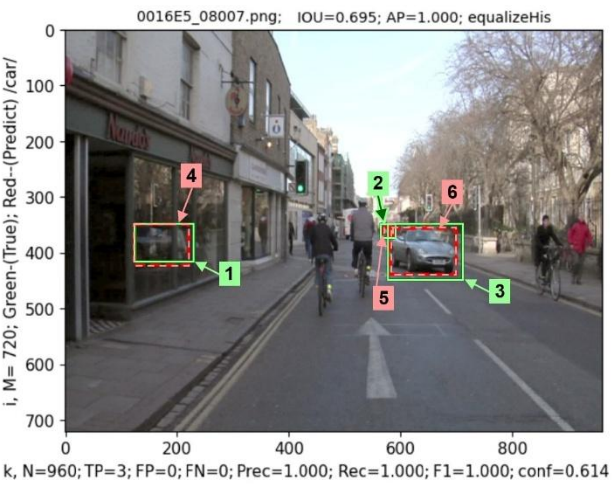

FIG. 3. Vehicle detection on the image after histogram equalization.

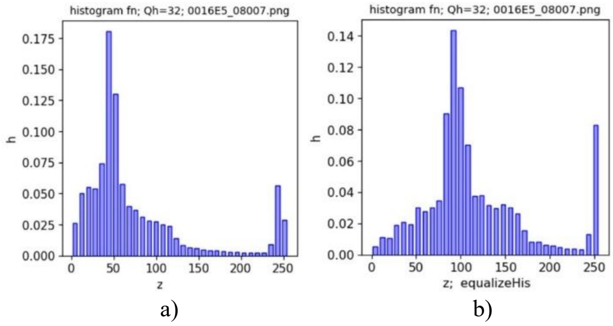

FIG. 4. The $h(z)$ of images: (a) original (Fig. 2) in grayscale; (b) image after histogram equalization (Fig. 3) in grayscale; histograms contain Qh intervals (bins).

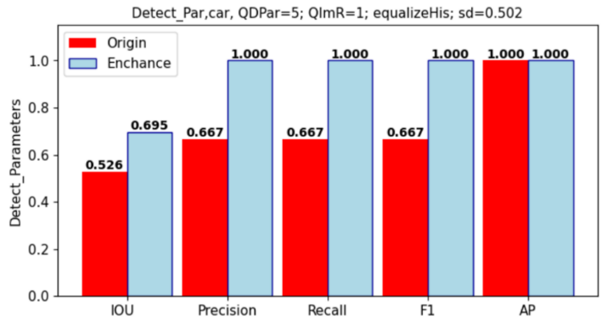

FIG. 5. Accuracy metrics of vehicle detection; Origin – on the original image (Fig. 2), Enhance – on the image after histogram equalization (Fig. 3).

Thus, the conducted studies confirmed the possibility of improving the accuracy of object detection on images by the YOLO network through image preprocessing, specifically histogram equalization and enhancement of local contrast.

V. CONCLUSION

Software was developed in the Python programming language on the Google Colab cloud platform for preliminary digital image processing of objects prior to their detection using the yolov8m model of the YOLO convolutional neural network. Preprocessing of images was carried out through histogram equalization and enhancement of local contrast. The original images were read from video cameras or graphic files. As a result of detection, the studied objects, in particular vehicles, were highlighted with rectangular bounding boxes. The accuracy of object detection was evaluated based on a set of parameters: Precision, Recall, IoU, AP, and F1. It was established that preprocessing of images, in particular histogram equalization, increases the accuracy of object detection. The increase in detection accuracy by the IoU parameter is 0.169, and by the F1 parameter is 0.333. The developed software can be applied in various computer vision systems as well as in Internet of Things systems for remote monitoring and control. It was shown that image preprocessing enables the detection of even small-sized objects, in conditions of shading and low contrast.

AUTHOR CONTRIBUTIONS

S.B. – conceptualization, writing-review and editing, supervision; S.S – methodology, software, resources, writing-original draft preparation, visualization, validation, investigation.

COMPETING INTERESTS

The authors declare no conflict of interest.

REFERENCES

[1] O. P. Stelmakh, I. V. Stetsenko, and D. V. Velyhotskyi, "Information Technology of Video Data Processing for Traffic Intensity Monitoring," *Control Systems & Computers*, vol. 3, pp. 50–59, 2020, doi: 10.15407/usim.2020.03.050.

[2] M. A. Z. Al Bayati and M. Çakmak, "Real-Time Vehicle Detection for Surveillance of River Dredging Areas Using Convolutional Neural Networks," *International Journal of Image, Graphics and Signal Processing (IJIGSP)*, vol. 15, no. 5, pp. 17–28, 2023, doi: 10.5815/ijigsp.2023.05.02.

[3] Zh. Hu, D. Uhryn, Yu. Ushenko, V. Korolenko, V. Lytvyn, and V. Vysotska, "System programming of a disease identification model based on medical images," in *Proc. SPIE: Sixteenth International Conference on Correlation Optics*, vol. 12938, pp. 129380F-1–129380F-4, 2024, doi: 10.1117/12.3009245.

[4] O. Berezsky, P. Liashchynskyi, O. Pitsun, P. Liashchynskyi, and M. Berezkyy, "Comparison of Deep Neural Network Learning Algorithms for Biomedical Image Processing," *CEUR Workshop Proceedings*, pp. 135–145, 2022.

[5] S. V. Balovsyak and I. M. Fodchuk, "Objects images alignment with the use of genetic and gradient algorithms," *International Journal of Computing*, vol. 12, no. 2, pp. 160–167, 2013, doi: 10.47839/ijc.12.2.597.

[6] S. V. Balovsyak, O. V. Derevyanchuk, Ya. V. Derevianchuk, V. V. Tomash, and S. V. Yarema, "Segmentation of railway transport images using fuzzy logic," *Trans Motauto World*, vol. 7, no. 3, pp. 122–125, 2022.

[7] S. Balovsyak, O. Kroitor, Kh. Odaiska, A. M. Salem, and S. Stets, "Car Image Recognition using Convolutional Neural Network with Effi-cientNet Architecture," in *IntelITSIS 2024: 5th International Workshop on Intelligent Information Technologies & Systems of Information Security*, Khmelnytskyi, Ukraine, Mar. 28, 2024, *CEUR Workshop Proceedings*, vol. 3675, pp. 182–195, 2024.

[8] Yu. Herman, H. Lastivka, and A. Samila, "Embedded Operating Systems in IoT Edge Computing," *Security of Infocommunication Systems and Internet of Things (SISIOT)*, vol. 2, no. 2, paper 02001, pp. 1–6, 2024, doi: 10.31861/sisiot2024.2.02001.

[9] "Model Prediction with Ultralytics YOLO," [Online]. Available: https://docs.ultralytics.com/modes/predict/#plotting-results.

[10] A. Farid, F. Hussain, K. Khan, M. Shahzad, U. Khan, and Z. Mahmood, "A Fast and Accurate Real-Time Vehicle Detection Method Using Deep Learning for Unconstrained Environments," *Applied Sciences*, vol. 13, no. 5, Article no. 3059, 2023. [Online]. Available: https://www.mdpi.com/2076-3417/13/5/3059.

[11] X. Li, Y. Wang, H. Zhang, and J. Liu, "Vehicle–Pedestrian Detection Method Based on Improved YOLOv8," *Electronics*, vol. 13, no. 11, Article no. 2149, 2024. [Online]. Available: https://www.mdpi.com/2079-9292/13/11/2149.

[12] J. P. Q. Tomas, A. Aquino, G. E. M. David, R. D. Del Ayre, and J. K. L. Alminiana, "YOLOv8-Based Vehicle Type Detection: An In-Depth Exploration of Deep Learning Techniques for Robust Analysis of Dashcam Footage," in *Proceedings of the 2024 9th International Conference on Information and Communication Technology*, pp. 91–96, 2024. [Online]. Available: https://dl.acm.org/doi/10.1145/3670085.3670098.

[13] R. Gonzalez and R. Woods, *Digital Image Processing*, 4th ed. New York, NY, USA: Pearson/Prentice Hall, 2018.

[14] S. Palani, *Principles of Digital Signal Processing*. Cham, Switzerland: Springer, 2022.

[15] D. Kim and D. Hwang, Eds., *Intelligent Imaging and Analysis*. Basel, Switzerland: MDPI, 2020.

[16] A. Geron, *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*. Sebastopol, CA, USA: O'Reilly Media, Inc., 2019.

[17] S. Balovsyak, Kh. Odaiska, O. Yakovenko, and I. Iakovlieva, "Adjusting the Brightness and Contrast parameters of digital video cameras using artificial neural networks," in *Proc. SPIE: Sixteenth International Conference on Correlation Optics*, vol. 12938, pp. 129380I-1–129380I-4, 2024, doi: 10.1117/12.3009429.

[18] J. Redmon and A. Farhadi, "YOLOv3: An Incremental Improvement," *arXiv preprint*, 2018, arXiv:1804.02767. [Online]. Available: https://arxiv.org/abs/1804.02767.

[19] "Roboflow Annotation Tool," *Roboflow*. [Online]. Available: https://roboflow.com.

[20] D. Suresha and H. N. Prakash, "Data Content Weighing for Subjective versus Objective Picture Quality Assessment of Natural Pictures," *International Journal of Image, Graphics and Signal Processing (IJIGSP)*, vol. 9, no. 2, pp. 27–36, 2017.

[21] S. V. Balovsyak and Kh. S. Odaiska, "Automatic Highly Accurate Estimation of Gaussian Noise Level in Digital Images Using Filtration and Edges Detection Methods," *International Journal of Image, Graphics and Signal Processing (IJIGSP)*, vol. 9, no. 12, pp. 1–11, 2017, doi: 10.5815/ijigsp.2017.12.01.

[22] "CamSeq01 Dataset, Cambridge Labeled Objects in Video," [Online]. Available: http://mi.eng.cam.ac.uk/research/projects/VideoRec/CamSeq01.

Serhiy Balovsyak

In 1995, graduated from Chernivtsi State University. In 2018, defended his doctoral dissertation in the specialty "Computer systems and components". Currently, works as an associate professor at the Department of Computer Systems and Networks of Chernivtsi National University. Research interests include digital signal processing, programming, artificial neural networks.

ORCID ID: 0000-0002-3253-9006

Serhii Stets

In 2021, graduated from the National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute" with a degree in "Systems of Artificial Intelligence". In 2022, entered a PhD program in the specialty "Software engineering". Research interests include media processing, programming, and artificial neural networks.

ORCID ID: 0009-0007-0231-9970

SISIOT Journal | journals.chnu.edu.ua/sisiot

Попередня обробка зображень об’єктів перед їх детектуванням засобами нейронної мережі YOLO

Сергій Баловсяк[1,*], Сергій Стець[2]

[1]Кафедра комп’ютерних систем та мереж, Чернівецький національний університет імені Юрія Федьковича, Чернівці, Україна
[2]Кафедра програмного забезпечення комп'ютерних систем, Чернівецький національний університет імені Юрія Федьковича, Чернівці, Україна

*Автор-кореспондент (Електронна адреса: s.balovsyak@chnu.edu.ua)

АНОТАЦІЯ Розроблено програмне забезпечення на мові Python для попередньої цифрової обробки зображень об’єктів перед їх детектуванням за допомогою штучної нейронної мережі You Only Look Once (YOLO). Проведено детектування зображень об’єктів, а саме автомобілів та інших учасників дорожнього руху. Попередня обробка зображень виконувалася шляхом еквалізації їх гістограм та підвищенням локального контрасту. Початкові зображення зчитувалися з відеокамер або з графічних файлів. Детектування зображень виконано моделлю середнього розміру YOLOv8m згорткової нейронної мережі YOLO. У результаті детектування досліджувані об’єкти, зокрема, автомобілі, виділялися прямокутними рамками. Для оцінки точності детектування об’єктів використано ряд метрик (параметрів): Precision, Recall, Intersection over Union (IoU), F1, Average Precision (AP). Мережу YOLO попередньо навчено на наборі даних Common Objects in Context. Нейронна мережа YOLO повертає ймовірність розпізнавання об’єкта, координати його центру (x, y) на зображенні та ширину і висоту (w, h). Виявлені об’єкти виділяються прямокутними обмежувальними рамками. Встановлення положення об’єктів на зображеннях виконувано в ручному режимі за допомогою інструменту Roboflow, який дозволяє точно встановити просторове положення кожного об’єкту. Дослідження впливу попередньої обробки зображень об’єктів на точність їх детектування мережею YOLO виконано на прикладі типового зображення дорожнього руху. Після еквалізації гістограми вона стає більш симетричною і рівномірною, що підвищує візуальну якість навіть темних та світлих ділянок. За рахунок цього підвищено точність детектування об’єктів практично за всіма метриками (параметрами). Збільшення точності детектування за параметром IoU складає 0.169. Сумарне покращення точності детектування за параметрами IoU, F1, AP складає 0.502. Показано, що після попередньої обробки зображень точність детектування об’єктів підвищилася, тому детектування всіх автомобілів виконано правильно. Розроблене програмне забезпечення може застосовуватися у різноманітних системах комп’ютерного зору, а також у системах Інтернету речей для дистанційного моніторингу та контролю.

КЛЮЧОВІ СЛОВА цифрова обробка зображень, штучні нейронні мережі, YOLO, детектування об’єктів, програмне забезпечення.