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A METHOD AND SOFTWARE FOR LICENSE PLATE RECOGNITION

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The article presents a method for license plate recognition using segmentation through the YOLO detection system combined with a task-oriented approach to training and the use of real-world variable data arrays. The development of metropolises and the constant increase in the number of vehicles on the roads have led to a new level of requirements for road safety systems. Automation, without exaggeration, is the most prioritized direction for the development of these systems. Only through automation can road safety systems process the vast amount of information generated on roads daily. Moreover, automation gradually reduces human involvement in tasks that computational systems can perform with equivalent or greater accuracy. These achievements aim to minimize the influence of the human factor and reduce operational costs. This is particularly important for megacities but also applies to the transportation system as a whole.

The purpose of the research is to develop a method for automated license plate recognition to improve the accuracy of road safety systems by reducing error rates, minimizing the excessive use of computational resources during detection, and lowering the cost of such systems.

The object of the study is the process of developing automated software systems for ensuring road safety with integrated vehicle identification functionality.

To achieve the stated goal, the following objectives were defined: to develop a method for license plate recognition using a task-oriented approach to training combined with the YOLO detection system; to evaluate the impact of prior segmentation of license plates using a specially trained YOLO system on error rates and processing time, as well as to conduct experiments with the proposed training method on real-world images with variable environments to confirm its adequacy.

A comparative analysis of the task-oriented training method for the YOLO v5 detection system with the commonly used Optical Character Recognition (OCR)-only approach confirmed the advantages of the task-oriented method for solving license plate recognition tasks. Additionally, the impact of blurring on detection results using the OCR method was investigated.

The results of practical research confirm the correctness of the chosen methods for improving the efficiency of license plate recognition.

Key words: image recognition, image annotation, machine learning, YOLO, license plate recognition

1. Introduction

The sufficient development of metropolises and the constant increase in the number of vehicles on the roads have led to a new level of requirements for road safety systems. Automation, without exaggeration, represents the highest-priority direction for the development of these systems. Only through automation can road safety systems handle the vast amount of information generated on roads daily. Furthermore, automation enables the gradual reduction of human involvement in tasks where computational systems can perform with equivalent or greater precision. Such advancements aim to minimize the influence of human error while also reducing operational costs. This is particularly crucial for metropolises but is also applicable to the transport system as a whole.

Current research in artificial intelligence and computer vision is highly relevant and widely discussed, showing great promise in providing tools for the partial or complete automation of road safety processes. These technologies also enhance the efficiency of existing systems.

However, despite significant progress in the automation of road safety systems using modern OCR (Optical Character Recognition) only technologies, challenges persist in vehicle license plate recognition (LPR) due to unpredictable and multifactorial road conditions. In some instances, recognition is impossible due to objective factors. In others, where recognition tasks cannot be satisfactorily achieved using existing approaches, neural networks' capabilities in pattern recognition provide a viable solution.

The recognition of license plates from road camera data typically involves four stages: first, image normalization; second, designation of the number plate region; third, recognition and reading of the text data; and finally, validation of the recognized data. Region detection plays a critical role in this process, directly impacting the effectiveness of subsequent stages. In situations where stages three and four cannot be completed due to objective constraints, accurate designation of the number plate region alone may suffice for the system to respond appropriately. For this reason, the efficiency and importance of the region detection process will be the primary focus of this article.

2. Literature review and problem statement

LPR process starts with graphical image processing obtained from road cameras. An important consideration, whether using an OCR-only approach or an enhanced approach with additional detection layers, is to verify the presence of a license plate in the image. Failing to do so may result in the processing of license plate empty images, leading to unnecessary time and resource consumption and, in some cases, data loss.

The paper [2] examines the Iterative Threshold Segmentation (ITS) Algorithm for vehicle number plate recognition techniques. It describes the use of an iteration-based thresholding approach to distinguish the image foreground from the background. Outdoor images depicting vehicles were employed for testing purposes. The results of automatic threshold processing on the experimental images demonstrate the method's validity. While this study represents an important contribution to enhancing the LPR process, the selection of experimental images and the emphasis on their diversity are insufficient to support claims of a significant improvement in precision.

The article [3] explores a potential solution to the Automatic LPR problem. It highlights that OCR-based approaches are prone to errors in specific scenarios, such as font variability and image segmentation through thresholding. Each of these issues is analyzed using a “problem-solution” framework. For example, the challenge of missing letter character templates is addressed by proposing the addition of supplementary templates. While the continuous development of the OCR database offers a viable solution, it remains limited due to the variability and unpredictability of letter distortions in real-world conditions. Moreover, in some cases, the OCR-based approach is too slow to meet the requirements of real-time applications, which are often essential in the LPR process.

The authors of article [4] propose the RL-OLD model, which employs reinforcement learning to optimize unloading decisions. This model is designed for high-precision license plate detection and recognition while ensuring efficient use of computational resources. It utilizes edge computing effectively for the detection of various types of license plates. The specific characteristics of a plate determine whether the detection-related computations are performed locally or in the cloud, depending on the complexity of the process. The proposed approach achieves a high level of accuracy, minimal data loss, and low latency.

Furthermore, the approach offers a flexible architecture suitable for both local and global deployments, depending on the system’s objectives. However, large-scale deployment of this architecture may prove cost-ineffective in certain scenarios compared to alternative solutions. Additionally, the use of YOLO v3 for license plate region detection is considered outdated, and newer versions of CNN-based detection systems should be explored.

The article [5] addresses the challenges of image processing approaches for Automatic Number Plate Recognition (ANPR) systems. The authors propose an efficient method for automatic number plate recognition, which involves processing input graphical data of vehicles through a series of sequential stages.

Initially, the input data undergoes filtering using an iterative bilateral approach. This is followed by adaptive histogram equalization. In subsequent steps, number plate extraction is achieved through image subtraction, bounding box analysis, detection of Sobel vertical edges, morphological operations, and image thresholding/binarization.

According to the authors, the proposed method demonstrates notable performance under challenging conditions, including digital noise, low illumination in the filmed area, blurry images, low contrast, and both underexposed and overexposed images. While the methods outlined in the research are effective for solving LPR tasks under the stated conditions, they require significant computational power and the involvement of advanced software engineering technologies.

The article [6] serves as a critical evaluation of LPR systems and emerging technological approaches in the field. It discusses the most effective detection methods and evaluates MATLAB-specific techniques, presenting the corresponding results. A case study is included, outlining the general steps of the LPR process.

However, many of the methods described fall within the domain of image processing, which is limited by relatively slow performance. Additionally, the study lacks large-scale experiments with a sufficiently representative and diverse dataset, which diminishes the reliability of the findings.

The article [7] examines a modern approach to solving the LPR task. It proposes a multi-stage process, from acquiring the image to outputting the plate's characters as ASCII text. These stages include vehicle region detection, license plate region detection, character segmentation, and recognition of characters within the segmented regions.

The authors claim that their method achieved 100% accuracy in license plate detection and 97.5% accuracy in character recognition. Furthermore, they assert that the proposed approach outperforms methods developed in recent years in terms of both speed and accuracy. The method incorporates the latest technologies across all stages of the LPR detection process.

However, the authors do not provide details about the evaluation datasets used during their experiments, raising questions about the basis for the reported accuracy levels.

The reviewed literature indicates that none of the proposed approaches utilize real-world image data to validate their claims. Moreover, no approach establishes a link between annotation quality and training effectiveness in addressing recognition tasks. Additionally, none of the approaches propose software-based solutions to enhance the accessibility of large-scale image dataset processing for task-specific training. Furthermore, no approach includes a review of error detection. Therefore, it can be concluded that studying a method to enhance LPR through a purpose-driven, software-based training approach is both reasonable and warranted.

3. The aim and objectives of the study

The purpose of this study is to develop a method for automated LPR to enhance the precision of road safety systems by reducing error rates, minimizing excessive use of computational resources during the detection process, and making such systems more cost-effective.

The object of the research is the process of developing automated software systems for road safety, incorporating vehicle identification functionality.

To reach the designated target following tasks were specified:

– to develop a method for LPR using a purpose-driven training approach combined with a YOLO detection system;

– to evaluate the impact of prior license plate segmentation using a custom-trained YOLO detection system on error rates and time costs, and to conduct experiments employing the proposed training method with environmentally variable real-world images as proof of adequacy.

4. Method for license plate recognition with segmentation and task-specific train approach

4.1. A review of the key weaknesses of the current OCR-only approach

OCR-only approach when it comes to LPR is very dependable on environmental conditions like light level, capturing device focusing, shooting speed, etc. When conditions are rough OCR-could fail, so license plate won't be recognized correctly.

To validate the stated claims, a dataset of 1,500 license plate images was collected and processed using OCR. Ten different levels of Gaussian blur were applied to evaluate precision under varying conditions. This approach simulates the insufficient focusing precision of photo-fixation cameras in real-world operating conditions within road safety systems. The visualization of blur levels and the corresponding OCR detection precision, as related to the blur levels, is presented in Figures 1 and 2.

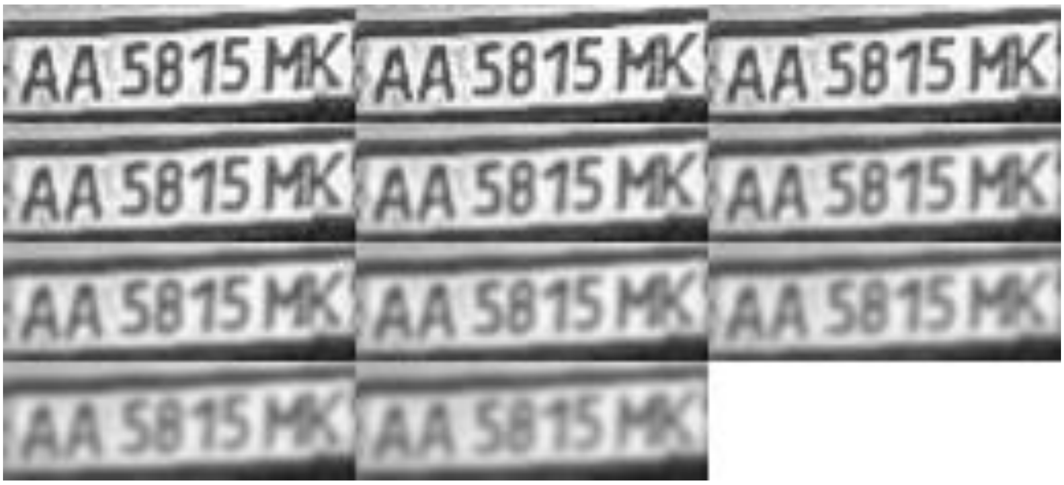

Fig. 1. Image blur levels visualization: Without blur and blur levels 1 – 10

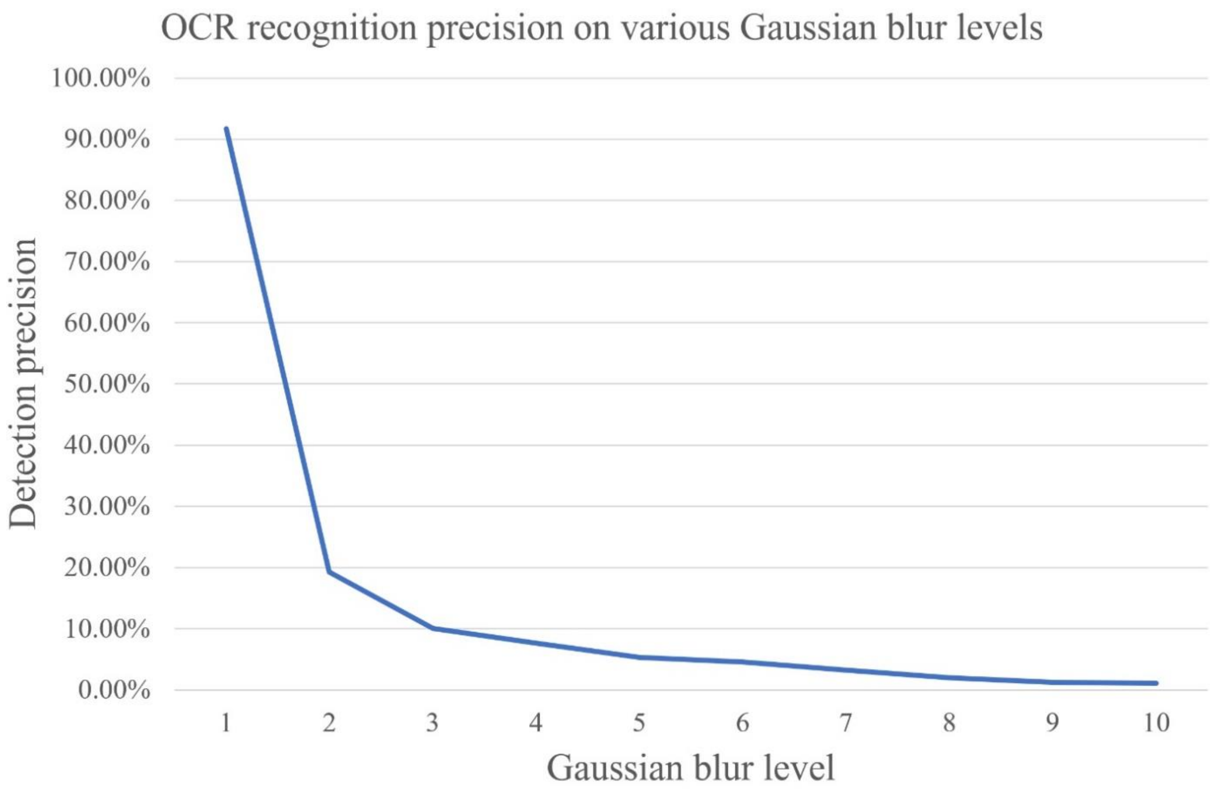

Fig. 2. Dependency graph for detection precision to blur level relation.
Precision decrease is a negative trend

As seen on graph that even least blur causing significant detection precision degradation when using OCR.

4.2. A review of segmentation using a task-specific training approach

The way to constrict detection region to license plate region only instead of whole image OCR processing proposed to solve this problem. But at the same time total consumptions for the process of license plate region detection and LPR should not exceed OCR-only processing time. The dependence is shown in the formula:

$$\Delta t_{RS} + \Delta t_{RO} < \Delta t_{OCR}, \quad (1)$$

where Δt_{RS} - average region detection time, Δt_{RO} – average OCR-processing time for region, Δt_{OCR} – whole image average OCR-processing time

Also license plate region detection and license plate detection total precision level should not degrade comparing to OCR-only detection on the same image. The dependence is shown in formula:

$$\frac{(P(RS) + P(RO))}{2} \geq P(OCR). \quad (2)$$

Therefore, region detection precision should be not less than 90% as in accordance with the standard $P(OCR)$ is defined as 90% [1].

As the existing systems currently in production adhere to standards and guarantee a detection precision, $P(OCR)$, of no less than 90%, it can be inferred that the OCR processing precision for the detected region only, $P(RO)$, is also no less than 90%.

4.3 A review of task-specific training approach

A review of publicly available image annotation software [8] has been conducted, with various metrics evaluated and proposed enhancements justified.

As a result of studying the problem of image classification for training using the existing software engineering tools of the .NET platform, the YoloAnno application [9] was proposed and developed. The final appearance of the application's workspace is presented in Figure 3.

Fig. 3. YoloAnno software application working area.

5. Experimental results of the proposed purpose-driven training method and software, utilizing real-world data

To conduct the experiment, a set of practical tasks was defined in the form of guidelines:

– build a hardware and software system that conforms to the Ukrainian national standard for capturing real-world public road environments;

– collect a comprehensive real-world image dataset, with or without license plates captured;

– review existing markup tools and propose a task-specific software solution for markup, demonstrating improved efficiency through a comparative analysis of current solutions;

– implement the proposed approaches in the markup application YoloAnno;

– classify 2,000 images using YoloAnno and create a YOLO-ready annotated training dataset;

– identify suitable training parameters to meet the desired error rate threshold and perform training;

– use the obtained training data to process a dataset of 20,000 real-world images;

– define task-specific detection result states and process the detection results accordingly;

– review the obtained results using diagrams and evaluate the validity of the stated hypotheses.

Following the completion of all implementation stages, including a system for graphical data collection, the YoloAnno software for image annotation, the collection of 2 million real-world images, and more, an experiment was conducted.

2000 environmentally variable images out of 2 million collected were classified with YoloAnno. The classification process resulted in the creation of a Yolo-format training input dataset. The environment was configured using the created dataset to train a Yolo v5 detection system based on a convolutional neural network. The training was successfully completed, and the results were tested on a separate testing dataset, confirming compliance with the specified requirements.

Statistical states have been defined to describe the results of image processing by the detection system. These states demonstrate compliance with the assigned tasks and the hypotheses proposed, as shown in Table 1.

Table 1. Statistical states of image processing using a Yolo detection system pre-trained with the proposed approach

#	**Visual assessment of the image**	**Detection result**
1	Image does not contain license plates	License plate was not detected
2	Image does not contain license plates	Erroneous detection
3	Image contains license plates	All license plates have been detected
4	Image contains license plates	Some (not all) license plates have been detected
5	Image contains license plates	None license plates has been detected

Following the definition of the resulting states, 20,000 images were processed. The obtained results were visually categorized in accordance with the five states defined above. The detection results are presented in Table 2 and Figure 4.

Table 2. Detection with pre-trained neural network success statistics

Statistical state	**Quantity, pcs.**	**Quantity, %**
1	13008	65,04
2	42	0,21
3	6643	33,21
4	222	1,11
5	86	0,43

From the detection validity perspective, the chart sectors are defined as follows: sectors 1 and 3 represent valid detections; sector 4 indicates partially valid detections; and sectors 2 and 5 correspond to invalid detections or cases where detection failed despite the object being present.

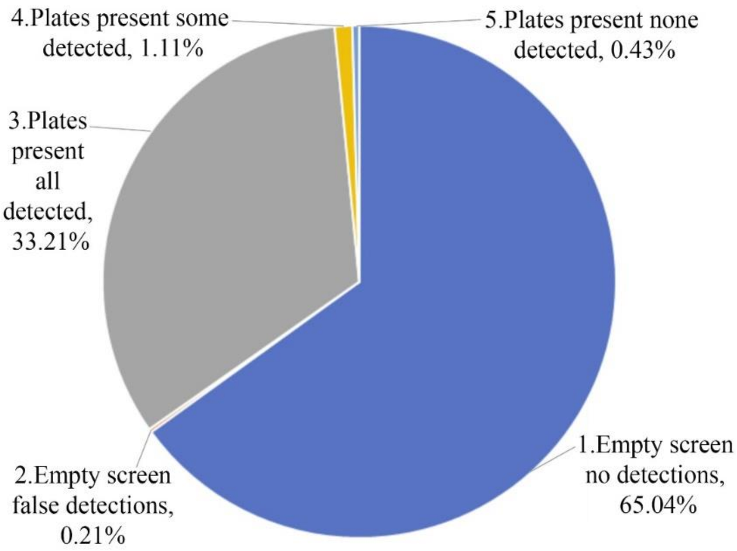

Fig. 4. Results of processing 20,000 images collected by the built system.

Figures 5 – 9 present sample images of detection results for each statistical state, along with the corresponding percentage for each state within the overall dataset.

Fig. 5 Image does not contain license plates - license plates were not detected (65,04%)

Fig. 6 Image does not contain license plates - erroneous detection (0,21%)

Fig. 7 Image contains license plates - all license plates have been detected (33,21%)

Fig. 8 Image contains license plates - some (not all) license plates have been detected (1,11%)

Fig. 9 Image contains license plates - None license plates have been detected (0,43%).

Based on the results obtained, **98.25%** of detections were correct, **1.11%** were partially correct, and **0.64%** were erroneous or failed to detect the object despite its presence.

Additionally, it is important to consider the statistics for images within the processed dataset that contain license plates, excluding those where vehicles and, consequently, license plates are absent. These refined statistics are presented in Figure 10.

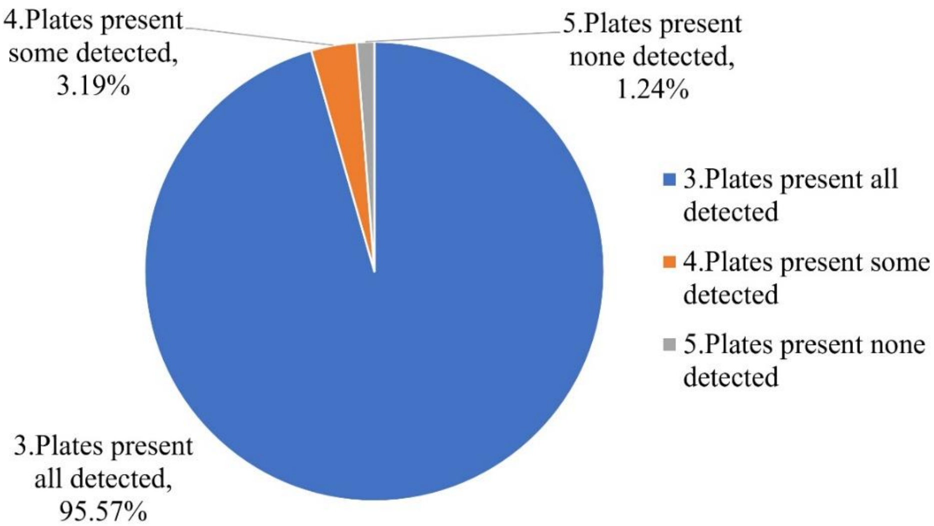

Fig. 10. Statistics for images containing license plates only.

Based on the results for images containing license plates only, **95.57%** of detections were correct, **3.19%** were partially correct, and **1.24%** were erroneous or failed to detect the object despite its presence.

Pivot Table 3 presents accuracy indicators, showing the resulting $P(RS)$ values for license plate region detection across all images and for images containing license plates only.

Table 3. Region detection accuracy indicators

	Correct detection (%)	**Partially correct detection (%)**	**Erroneous detection (%)**
All images	98,25	1,11	0,64
Only images with license plates present	95,57	3,19	1,24

Detection time was measured while processing images with a resolution of 1280 × 800 pixels, regardless of the number of license plates in each image. A Yolo v5-based pre-trained neural network-based detection system was utilized on a personal computer, with the results presented in Table 3.

The data in the table indicate that the use of the approach, resulting in training data for detection tasks, demonstrates characteristics of a real-time system. Consequently, it can be concluded that detection can occur in real time. For instance, this capability could be applied to the real-time processing of video streams captured by road cameras.

To measure the time required for full-image OCR processing (Δt_{OCR}) and neural network pre-processed region-only OCR processing (Δt_{RO}), a dataset of 1,500 images was collected using the built hardware system and processed. The resulting processing times, along with the previously obtained region detection results (Δt_{RS}), are presented in Table 3 and Figure 11.

Table 3. Processing times for images captured by road camera

	t_{min} (sec.)	t_{max} (sec.)	t_{avg} (sec.)
Δt_{OCR}	0,592	19,969	3,989
Δt_{RO}	0,333	2,125	0,517
Δt_{RS}	0,555	0,867	0,651
$\Delta t_{RS} + \Delta t_{RO}$	0,888	2.992	1,168

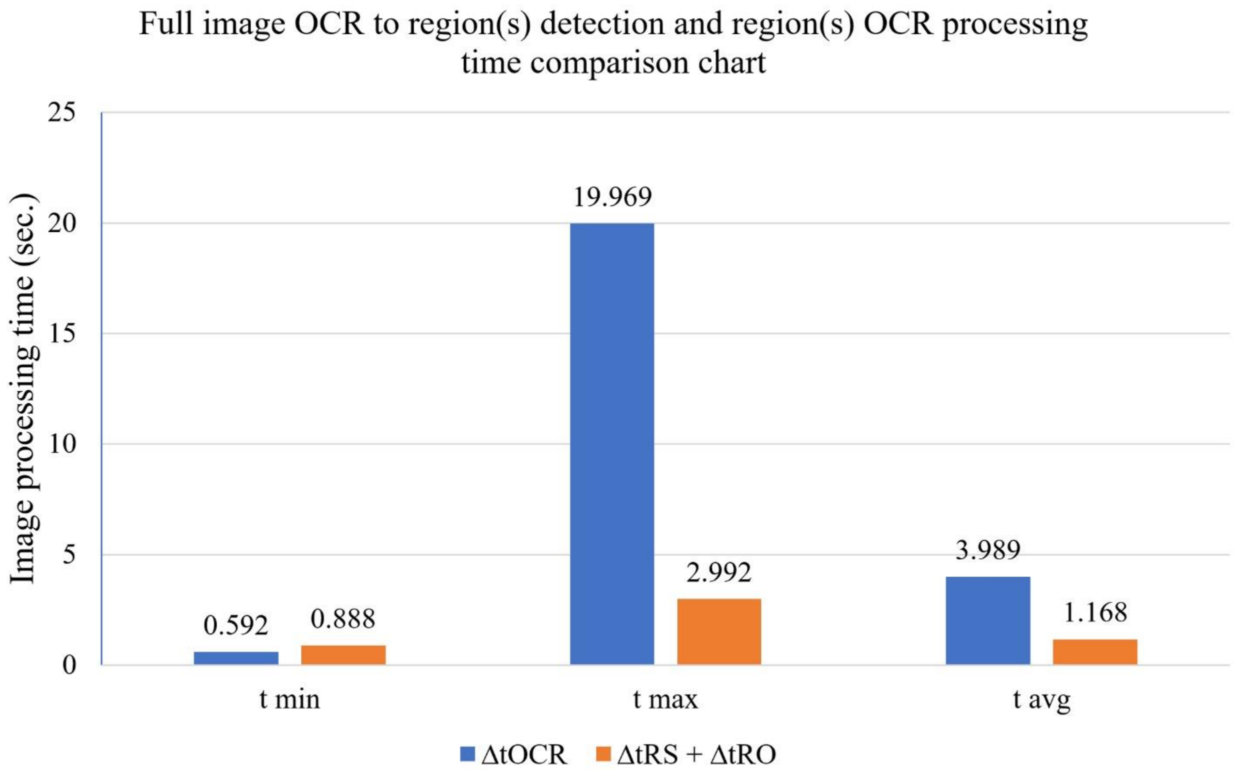

Fig. 11. Comparison of OCR processing alone and OCR with region detection processing results, where longer image processing times indicate a negative trend.

Based on the experimentally obtained results shown in Figure 11, it can be concluded that the neural network-based region detection mechanism enhances the LPR process. This approach not only improves detection precision but also reduces processing time.

6. Discussion of the results of the study of proposed purpose-driven training method for license plate recognition

The role of the pattern recognition process in license plate region detection has been critically reviewed within the framework of vehicle LPR for road safety systems.

The key stages of the process, highlighted challenges, and potential avenues for improvement were outlined to elucidate the core aspects of the LPR process. Features and limitations of existing systems were identified following a review of current methodologies and adherence to DSTU 8809:2018 standards.

Optimization criteria were defined, alongside the conditions under which the proposed approaches could outperform existing methods. To validate these statements, a series of experiments were designed to either confirm or refute the hypotheses.

Artificial intelligence models were proposed for license plate region detection, with the YOLO v5 detection system employed as a representative example. A hardware system was developed for image capture within road infrastructure to generate a dataset consistent with those used by current road safety systems. This dataset was subsequently utilized to train the artificial intelligence models with the proposed task-specific software approach methodology.

The results obtained were compared against the initial optimization criteria, substantiating the feasibility and efficacy of the proposed approaches for achieving LPR tasks. The role of artificial intelligence models in enhancing the efficiency of the LPR process was conclusively demonstrated.

7. Conclusion

1. A comparative analysis of the use of method for LPR with segmentation and task-specific train approach using real world data obtained in accordance with Ukrainian national standard for capturing real-world public road environments on one side with OCR-only approach on another proves advantages of task-specific train approach method. Its ability to narrow down the processed during recognition area allows to decrease error rate and computational expenses.

2. A number of experiments has been conducted to check the dependence of error rate and computational expenses on LPR using real world data. Two approaches involving OCR-only and proposed method were investigated with environmentally variable images. It was found that pre-trained YOLO detection system involved into recognition process reduces impact of whole image processing compared to segmented one. This provides an average error rate decrease to 5.57% compared to OCR-only approach [1]. In addressing the LPR task, the YOLO system demonstrated numerous advantages: real-time image recognition with processing times ranging from 0.6 to 0.9 seconds per image on an average desktop PC using a CPU, regardless of the number of detection regions; notably faster performance when leveraging CUDA; an overall correct detection rate of 96%; an accessible training interface that simplifies the training process; and flexible training parameters to achieve the desired level of precision.

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МЕТОД ТА ПРОГРАМНІ ЗАСОБИ ДЛЯ РОЗПІЗНАВАННЯ НОМЕРНИХ ЗНАКІВ

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В статті представлений метод розпізнавання номерних знаків із використанням сегментації шляхом використання системи детектування *YOLO* у поєднанні із завдання-орієнтованим підходом до процесу навчання та використанням масивів варіативних даних реального світу.

Розвиток мегаполісів і постійне збільшення кількості транспортних засобів на дорогах призвели до нового рівня вимог до систем безпеки дорожнього руху. Автоматизація, без перебільшення, є найбільш пріоритетним напрямком розвитку цих систем. Лише за допомогою автоматизації системи безпеки дорожнього руху можуть обробляти величезну кількість інформації, що генерується на дорогах щодня. Крім того, автоматизація дозволяє поступово зменшувати участь людини в задачах, які обчислювальні системи можуть виконувати з еквівалентною або більшою точністю. Ці досягнення спрямовані на мінімізацію впливу людського фактору, а також на зниження експлуатаційних витрат. Це особливо важливо для мегаполісів, але також стосується транспортної системи в цілому.

Метою дослідження є розробка методу автоматизованого розпізнавання номерних знаків для підвищення точності систем забезпечення дорожньої безпеки шляхом зниження рівня помилок, мінімізації надмірного використання обчислювальних ресурсів у процесі виявлення та здешевлення таких систем. Об'єктом дослідження є процес розробки автоматизованих програмних систем для забезпечення дорожньої безпеки з інтеграцією функціоналу ідентифікації транспортних засобів.

Для досягнення поставленої мети були визначені такі завдання: розробити метод розпізнавання номерних знаків із застосуванням цілеспрямованого підходу до навчання у поєднанні з системою виявлення *YOLO*; оцінити вплив попередньої сегментації номерних знаків із використанням спеціально навченої системи *YOLO* на рівень помилок і часові витрати, а також провести експерименти із застосуванням запропонованого методу навчання на реальних зображеннях із варіативним довкіллям для підтвердження його адекватності.

Порівняльний аналіз використання завдання-орієнтованого методу навчання системи детектування на базі *YOLO v5* лише з загальноприйнятим методом оптичного розпізнавання символів (Optical Character Recognition, OCR) підтвердив переваги завданняорієнтованого методу при вирішенні завдання з розпізнавання номерних знаків. Також було досліджено вплив розмиття на результати детектування із використанням *OCR* методу.

Результати практичних досліджень підтверджують правильність обраних методів для підвищення ефективності розпізнавання номерних знаків.

Ключові слова: розпізнавання зображень, анотація зображень, машинне навчання, YOLO, розпізнавання номерних знаків