: 2582-4686 SJIF 2021-3.261,SJIF 2022-2.889, 2024-
5 ResearchBib IF: 8.848 / 2024

THE MULTIDISCIPLINARY JOURNAL OF SCIENCE AND TECHNOLOGY

VOLUME-4, ISSUE-8

Effect of Frame Processing Frequency on Object Identification Using MobileNetV2 Neural Network for a Mobile Robot

Dmytro Gurin [1], Vladyslav Yevsieiev [1], Amer Abu-Jassar [2], Svitlana Maksymova [1]

[1] Department of Computer-Integrated Technologies, Automation and Robotics, Kharkiv National University of Radio Electronics, Ukraine

[2] Faculty of Information Technology, Department of Computer Science, Ajloun National University, Ajloun, Jordan

Abstract: This article is devoted to the analysis of the relationship between frame processing frequency, identification speed, recognition accuracy and system resources. The article presents a mathematical description of the dependencies, which allows for a quantitative assessment of the effect of changing the processing frequency on these parameters. A program code based on the Python language was developed, which integrates the MobileNetV2 model for practical testing and optimization. The conducted experiments allow us to identify optimal settings that provide a balance between recognition accuracy and processing speed, taking into account system resources. The results of the study provide useful recommendations for improving computer vision systems in mobile robots.

Key words: Industry 4.0, Mobile Robots, Work Area, Computer Vision, Frame Processing Frequency, Identification Speed, Recognition Accuracy

Introduction

In the conditions of rapid development of mobile robotics technologies, the efficiency of object identification systems is critically important for ensuring the accuracy and reliability of robots [1]-[11]. Neural network models [12]-[18], in particular MobileNetV2, show significant potential in real-time object recognition due to their ability to process large amounts of information at high speed. Therefore, different methods and approaches can be used here [19]-[40]. However, reducing latency in video processing and increasing identification speed are key factors to achieve real-time in robotics systems.

Based on this study of the effect of frame processing frequency on the accuracy and speed of object identification based on MobileNetV2, it is possible to find out how different levels of frame processing frequency affect the recognition results and the efficiency of the system as a whole. The analysis of frame processing frequency will not only allow determining the optimal parameters for real-time systems, but will also provide an opportunity to improve algorithms for mobile robots, which is critical for their integration into complex environments. The research results will contribute to improving the accuracy of object recognition and reducing delays, which is important for improving the productivity and reliability of mobile robots in real operating conditions.

Related works

In the modern world, the problem of identifying objects is very acute, especially with the widespread robotization of production, the social sphere and everyday life. Let's look at several recent scientific works on this topic.

Let us begin with the fact that combination of machine vision and robotics to achieve the same precise and fast grasping as that of humans requires high-precision target detection and recognition, location and reasonable grasp strategy generation, which is the ultimate goal of global researchers and one of the prerequisites for the large-scale application of robots [41]. Bai, Q., and co-authors in [41] provide a systematic summary and analysis of the research status of machine vision and tactile feedback in the field of robot grasping and establishes a reasonable reference for future research.

We have to note that object identification may be provided not only by computer vision but by integration of quadruple tactile sensors. Tactile sensors can enable a robotic manipulator to identify the object in contact [42], [43]. Authors in [42] present their robot hand with tactile perception that can improve the safety of object manipulation and also improve the accuracy of object identification.

The study [43] demonstrates the potential of hybrid tactile sensor to improve the artificial intelligence of robots, in particular their ability to distinguish objects in complex settings and sorting them effectively.

The article [44] proposes an object detection method for grasping robot based on improved YOLOv5 in order to achieve more accurate positioning and recognition of objects.

Scientists in [45] consider the implementation of an autonomous robotic system for the categorization and physical sorting of recyclables according to material types. They focus on the development of a low-cost computer vision module based on deep learning technologies to identify and sort items.

Researchers in [46] provide a systematic review of computer vision-based holistic scene understanding in HRC scenarios, which mainly takes into account the cognition of object, human, and environment along with visual reasoning to gather and compile visual information into semantic knowledge for subsequent robot decision-making and proactive collaboration.

Peculiarities of the influence of frame processing frequency on the accuracy and speed of object identification in computer vision systems

When developing a computer vision system for a mobile robot, especially when studying the effect of frame processing frequency on the accuracy and speed of object identification based on the MobileNetV2 neural network, it is necessary to take into account a number of features that affect the system's efficiency. These features include a mathematical description of the dependencies between frame rate, identification speed, recognition accuracy, and system resources. Let us describe these dependencies in the form of mathematical expressions:

- the frequency of frame processing, or Frame Rate (FR), determines the number of frames that are processed by the system per unit of time. It is measured in frames per second (FPS). The effect of the frame rate on the delay in the computer vision system can be described as:

$$T_{delay} = 1/FPS \qquad (1)$$

T_{delay} – delay, measured in seconds. Decreasing latency is critical for real-time systems, as it reduces the time between image acquisition and processing;

FPS – speed, frames per second.

For example, at a frequency of 30 FPS, the delay will be approximately 33.3 ms, while at a frequency of 60 FPS, the delay decreases to 16.7 ms.

- the speed of object identification, it is determined by the time required to process one frame. It depends on the frame processing frequency and the complexity of the neural network model. The correspondence between the speed of identification and the frequency of frame processing can be described as:

$$T_{Procesing\_one\_frame} = T_{ident}/FPS \qquad (2)$$

$T_{Procesing\_one\_frame}$ - one frame processing MobileNetV2 model, which can be significant depending on the model size and hardware resources. To ensure optimal performance, it is important to optimize the model and hardware to reduce frame processing time.

- the accuracy of object recognition depends on the quality of the model and the frequency of frame processing. Increasing the frequency of frame processing can lead to improved recognition accuracy by reducing the possibility of missing objects due to insufficient frequency. However, at a high processing frequency, there may be problems with the load on the hardware. Precision time;

T_{ident} - identification time.

: 2582-4686 SJIF 2021-3.261,SJIF 2022-2.889, 2024-
5 ResearchBib IF: 8.848 / 2024
THE MULTIDISCIPLINARY JOURNAL OF SCIENCE AND TECHNOLOGY
VOLUME-4, ISSUE-8

As can be seen from expression 2, the time for object identification includes the time for image processing through the can be described in terms of a metric such as Precision, Recall, or F1-Score (weighted average precision and completeness). These metrics can be expressed as:

$$Precision = TP/(TP+FP) \tag{3}$$

$$Recall = TP+FN \tag{4}$$

$$F_{1Score} = 2 * \frac{\Pr ecision * Reecal}{\Pr ecision + Reecal} \tag{5}$$

TP - True Positives;
FP - False Positives;
FN - False Negatives.

- delay reducing and increasing the frequency of processing frames is often accompanied by an increase in the load on the processor and energy consumption. It is important to consider the resource limitations of the mobile robot, as high processing requirements can lead to faster battery discharge and system overheating. Energy costs can be estimated as:

$$E_{expend} = T_{Procesing\_one\_frame} * E_{frame} \tag{6}$$

E_{expend} - energy costs;
$T_{Procesing\_one\_frame}$ - processing time of one frame;
E_{frame}- energy consumption for frame processing may vary depending on the complexity of the model and processing frequency.

In order to achieve an optimal balance between accuracy, speed and resources, various optimization methods can be applied, such as reducing the size of the model, using specialized hardware accelerators or parallel frame processing. Calculating the optimal frame rate can also include using profilers to measure real-world system performance and adjust processing parameters in real time.

Software implementation of object recognition and identification in Python and conducting experimental research

The choice of the Python language for the study of the influence of frame processing frequency on the identification of objects based on the MobileNetV2 neural network for a mobile robot is due to its numerous advantages in the field of machine learning and computer vision. Python is widely used due to its easy syntax and a large number of libraries, such as TensorFlow and OpenCV, which provide powerful tools for working with neural networks and image processing. The TensorFlow library offers a convenient interface for loading and using pre-trained models, such as MobileNetV2, which simplifies the process of model implementation and testing. OpenCV, on the other hand, provides powerful tools for video and image processing, which is critical for working with real video streams from a mobile robot. Python also makes it easy to integrate these libraries, creating a convenient environment for experimenting with different frame processing options and evaluating their impact on identification accuracy and speed. A better understanding and optimization of such parameters in real time is key to achieving high performance of a computer vision system. Which provides efficiency and flexibility during system development and improvement, which is essential for successfully achieving research objectives. The main code fragments of the developed program for the study of the influence of frame processing frequency in the identification of objects based on the MobileNetV2 neural network model for a mobile robot are given below with an explanation.

```
class_names = [
    'N/A', 'person', 'bicycle', 'car', 'motorcycle', 'airplane',
```

```
'bus', 'train', 'truck', 'boat', 'traffic light', 'fire hydrant',
'stop sign', 'parking meter', 'bench', 'bird', 'cat', 'dog',
'horse', 'sheep', 'cow', 'elephant', 'bear', 'zebra', 'giraffe',
'backpack', 'umbrella', 'handbag', 'tie', 'suitcase', 'frisbee',
'skis', 'snowboard', 'sports ball', 'kite', 'baseball bat',
'baseball glove', 'skateboard', 'surfboard', 'tennis racket',
'bottle', 'wine glass', 'cup', 'fork', 'knife', 'spoon', 'bowl',
'banana', 'apple', 'sandwich', 'orange', 'broccoli', 'carrot',
'hot dog', 'pizza', 'donut', 'cake', 'chair', 'couch', 'potted plant',
'bed', 'dining table', 'toilet', 'TV', 'laptop', 'mouse',
'remote', 'keyboard', 'cell phone', 'microwave', 'oven', 'toaster',
'sink', 'refrigerator', 'book', 'clock', 'vase', 'scissors',
'teddy bear', 'hair drier', 'toothbrush'
```

This piece of code defines a list of object classes that the neural network model can recognize. Each element in the list represents a specific type of object, for example "person" or "car", and corresponds to the index by which the model classifies the objects in the images.

```
def detect_objects(image):
    input_tensor = tf.convert_to_tensor(image, dtype=tf.uint8)
    input_tensor = input_tensor[tf.newaxis, ...]
    detections = model.signatures['serving_default'](input_tensor)
    return detections
```

The function `detect_objects` converts the image into a TensorFlow tensor, adds a new dimension to the batch, and uses the model to perform object recognition. The returned result contains information about the detected objects, including coordinates, classes, and probabilities.

```
frame_skip = 5
```

This piece of code sets the frame skipping interval when processing video, in this case every fifth frame is processed. This allows you to reduce the load on the system and speed up processing, while maintaining the efficiency of object recognition.

```
input_frame = cv2.resize(frame, (320, 320))
```

This piece of code resizes the frame to 320x320 pixels to prepare the image to be fed to a neural network model that expects input with certain dimensions. This ensures compliance with the model's requirements for correct processing.

```
if int(cap.get(cv2.CAP_PROP_POS_FRAMES)) % frame_skip == 0:
    start_time = time.time()
    detections = detect_objects(input_frame)
    end_time = time.time()
    print(f"Inference Time: {end_time - start_time:.3f}s")
```

This piece of code checks if the current video frame is worth processing based on the frame skip interval. If so, it runs image processing through the model, measures the execution time of that processing, and outputs that time to the console for performance monitoring.

```
num_detections = int(detections['num_detections'][0])
    detection_classes = detections['detection_classes'][0].numpy().astype(np.int64)
    detection_boxes = detections['detection_boxes'][0].numpy()
    detection_scores = detections['detection_scores'][0].numpy()
```

This piece of code extracts information about the number of detected objects, their classes, bounding box coordinates, and probabilities from the recognition results. This data is used for further processing and visualization of newly applied objects in the image.

The developed user interface of the program for researching the influence of frame processing frequency on object identification based on the MobileNetV2 neural network for a mobile robot is shown in Figure 1.

: 2582-4686 SJIF 2021-3.261,SJIF 2022-2.889, 2024-
5 ResearchBib IF: 8.848 / 2024
THE MULTIDISCIPLINARY JOURNAL OF SCIENCE AND TECHNOLOGY
VOLUME-4, ISSUE-8

Figure 1: The developed user interface of the object identification program based on the MobileNetV2 neural network for a mobile robot

On the basis of the developed program, a number of experiments were carried out to investigate the influence of frame processing frequency in the identification of objects based on the MobileNetV2 neural network model for a mobile robot. For the purity of the experiment, we note that the hardware consisted of the following elements: CPU Intel Core i7-6650U, 3.4 GHz; RAM – 16Mb; HDD - 512Gb; GPU Intel Iris Graphics 540. The obtained results are presented in Table 1, and for the convenience of visualizations for data analysis are presented in the form of graphs in Figure 2.

Table 1: Obtained during the testing of the influence of frame processing frequency during the identification of objects based on the MobileNetV2 neural network

Frame rate (frames/sec)	Identification speed (frames/sec)	Recognition accuracy (%)	CPU using (%)	GPU using (%)	Frame processing time (ms)
5	4.8	92.5	~35	~ 40	200
10	9.6	91.8	~45	~ 55	100
15	14.3	90.2	~ 55	~ 65	67
20	18.9	88.7	~ 65	~ 75	50
30	27.5	85.3	~75	~ 85	33
40	35.2	82.9	~ 85	~ 90	25

: 2582-4686 SJIF 2021-3.261,SJIF 2022-2.889, 2024-
5 ResearchBib IF: 8.848 / 2024

THE MULTIDISCIPLINARY JOURNAL OF SCIENCE AND TECHNOLOGY

VOLUME-4, ISSUE-8

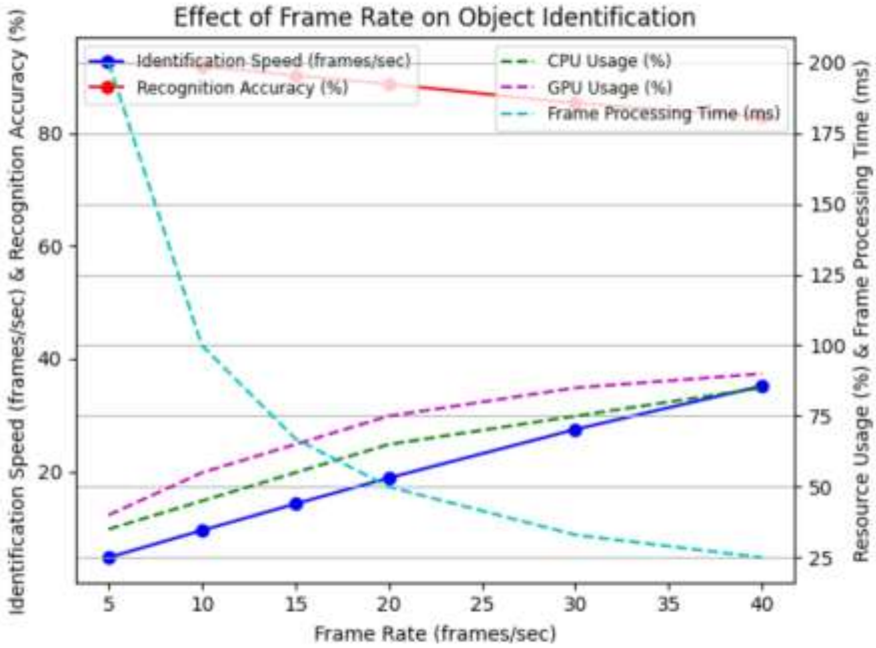

Figure 2: Combined graphs of comparison of obtained experimental results

Based on the results of testing the effect of frame processing frequency on object identification using the MobileNetV2 neural network, several key conclusions can be drawn. With an increase in the frequency of frame processing, the speed of object identification improves, which can be seen from the decrease in the processing time of each frame. However, an increase in the frequency of frame processing is accompanied by a decrease in recognition accuracy. This decrease in accuracy can be attributed to potential model overload and reduced frame processing time, resulting in less accurate predictions.

In addition, with an increase in the frame rate, the use of resources, both CPU and GPU, increases. The CPU and GPU usage metrics show a clear upward trend with increasing frame rates, indicating that more processing power is needed to process more frames. This increased load on system resources can lead to thermal throttling or other performance issues if not properly managed.

In conclusion, although increasing the frame rate can improve object identification speed, it also leads to a decrease in accuracy and an increase in resource consumption. It is important to strike a balance between identification speed, accuracy, and system resource usage to optimize performance and ensure the MobileNetV2 model works effectively on mobile robots.

Conclusion

As a result of the study of the influence of frame processing frequency on object identification using the MobileNetV2 neural network for a mobile robot, several important conclusions were obtained. Experiments have shown that increasing the frequency of frame processing has a positive effect on the speed of object identification, as the processing time of each frame decreases. However, with an increase in the frequency of frame processing, there is a decrease in recognition accuracy, which can be explained by insufficient time to analyze each frame.

At the same time, increasing the frequency of frame processing leads to an increase in the use of computing resources, in particular CPU and GPU. This increased load can cause performance issues such as system overheating. The results indicate the need to find an optimal balance between processing speed, recognition accuracy and resource consumption.

Overall, the study confirmed the importance of carefully tuning the frame rate to achieve high performance and efficiency of an object identification system, while considering the trade-offs between speed, accuracy and resources.

References:

1. Kuzmenko, O., & et al. (2024). Robot Model for Mines Searching Development. Multidisciplinary Journal of Science and Technology, 4(6), 347-355.
2. Yevsieiev, V., & et al. (2024). The Sobel algorithm implementation for detection an object contour in the mobile robot's workspace in real time. Technical Science Research in Uzbekistan, 2(3), 23-33.
3. Abu-Jassar, A., & et al. (2024). The Optical Flow Method and Graham's Algorithm Implementation Features for Searching for the Object Contour in the Mobile Robot's Workspace. Journal of Universal Science Research, 2(3), 64-75.
4. Yevsieiev, V., & et al. (2024). The Canny Algorithm Implementation for Obtaining the Object Contour in a Mobile Robot's Workspace in Real Time. Journal of Universal Science Research, 2(3), 7–19.
5. Maksymova, S., & et al. (2024). The Lucas-Kanade method implementation for estimating the objects movement in the mobile robot's workspace. Journal of Universal Science Research, 2(3), 187-197.
6. Yevsieiev, V., & et al. (2024). Using Contouring Algorithms to Select Objects in the Robots' Workspace. Technical science research in Uzbekistan, 2(2), 32–42.
7. Nevliudov, I. S., & et al. (2023). Conveyor Belt Object Identification: Mathematical, Algorithmic, and Software Support. Appl. Math. Inf. Sci. 17, 6, 1073-1088.
8. Abu-Jassar, A. T., Al-Sharo, Y. M., Lyashenko, V., & Sotnik, S. (2021). Some Features of Classifiers Implementation for Object Recognition in Specialized Computer systems. TEM Journal: Technology, Education, Management, Informatics, 10(4), 1645-1654.
9. Al-Sharo, Y. M., Abu-Jassar, A. T., Sotnik, S., & Lyashenko, V. (2021). Neural networks as a tool for pattern recognition of fasteners. International Journal of Engineering Trends and Technology, 69(10), 151-160.
10. Sotnik, S., Mustafa, S. K., Ahmad, M. A., Lyashenko, V., & Zeleniy, O. (2020). Some features of route planning as the basis in a mobile robot. International Journal of Emerging Trends in Engineering Research, 8(5), 2074-2079.
11. Гиренко, А. В., Ляшенко, В. В., Машталир, В. П., & Путятин, Е. П. (1996). Методы корреляционного обнаружения объектов. Харьков: АО "БизнесИнформ, 112.
12. Matarneh, R., & et al. (2017). Building robot voice control training methodology using artificial neural net. International Journal of Civil Engineering and Technology, 8(10), 523–532.
13. Maksymova, S., & et al. (2017). Software for voice control robot: example of implementation. Open Access Library Journal, 4, 1-12.
14. Bortnikova, V., & et al. (2019). Structural parameters influence on a soft robotic manipulator finger bend angle simulation. In 2019 IEEE 15th International Conference on the Experience of Designing and Application of CAD Systems (CADSM), IEEE, 35-38.
15. Mousavi, S. M. H., Victorovich, L. V., Ilanloo, A., & Mirinezhad, S. Y. (2022, November). Fatty liver level recognition using particle swarm optimization (PSO) image segmentation and analysis. In 2022 12th International Conference on Computer and Knowledge Engineering (ICCKE) (pp. 237-245). IEEE.
16. Orobinskyi, P., Petrenko, D., & Lyashenko, V. (2019, February). Novel approach to computer-aided detection of lung nodules of difficult location with use of multifactorial models and deep neural networks. In 2019 IEEE 15th International Conference on the Experience of Designing and Application of CAD Systems (CADSM) (pp. 1-5). IEEE.
17. Sotnik, S., & et al.. (2022). Analysis of Existing Infliences in Formation of Mobile Robots Trajectory. International Journal of Academic Information Systems Research, 6(1), 13-20.
18. Sotnik, S., & et al.. (2022). Modern Industrial Robotics Industry. International Journal of Academic Engineering Research, 6(1),. 37-46.

: 2582-4686 SJIF 2021-3.261,SJIF 2022-2.889, 2024-
5 ResearchBib IF: 8.848 / 2024
THE MULTIDISCIPLINARY JOURNAL OF SCIENCE AND TECHNOLOGY
VOLUME-4, ISSUE-8

19. Dobrovolskaya, I., & Lyashenko, V. (2013). Interrelations of banking sectors of European economies as reflected in separate indicators of the dynamics of their cash flows influencing the formation of the resource potential of banks. European Applied Sciences, 1-2, 114-118.

20. Работягов, А. В., Ляшенко, В. В., & Кобылин, О. А. (2016). Сегментация сложных изображений цитологических препаратов, Радиотехника: Всеукр. межвед. науч.-техн. Сб., 185, 87-94.

21. Kots, G. P., & Lyashenko, V. (2012). Banking sectors of the economies of European countries in the representation of statistical interrelation between indices that characterize their development. European Applied Sciences, 1, 461-465.

22. Kuzemin, A., & Lyashenko, V. (2009). Methods of comparative analysis of banks functioning: classic and new approaches. Information Theories & Applications, 16(4), 384-396.

23. Ляшенко В. В. (2007). Интерпретация и анализ статистических данных, описывающих процессы экономической динамики. Бизнес Информ, 9(2), 108-113.

24. Слюніна, Т. Л., Бережний, Є. Б., & Ляшенко, В. В. (2007). Розвиток вітчизняної мережі банківських установ: особливості та регіональні аспекти. Вісник ХНУ ім. В. Н. Каразіна. Економічна серія, 755. 84–88.

25. Putyatin, Y. P., & et al.. (2016) The Pre-Processing of Images Technique for the Material Samples in the Study of Natural Polymer Composites. American Journal of Engineering Research, 5(8), 221-226.

26. Lyashenko, V., Matarneh, R., & Kobylin, O. (2016). Contrast modification as a tool to study the structure of blood components. Journal of Environmental Science, Computer Science and Engineering & Technology, 5(3), 150-160.

27. Lyubchenko, V., & et al.. (2016). Digital image processing techniques for detection and diagnosis of fish diseases. International Journal of Advanced Research in Computer Science and Software Engineering, 6(7), 79-83.

28. Lyashenko, V. V., Matarneh, R., Kobylin, O., & Putyatin, Y. P. (2016). Contour Detection and Allocation for Cytological Images Using Wavelet Analysis Methodology. International Journal, 4(1), 85-94.

29. Lyashenko, V., Kobylin, O., & Ahmad, M. A. (2014). General methodology for implementation of image normalization procedure using its wavelet transform. International Journal of Science and Research (IJSR), 3(11), 2870-2877.

30. Sotnik, S., & Lyashenko, V. (2022). Prospects for Introduction of Robotics in Service. Prospects, 6(5), 4-9.

31. Al-Sharo Y., & et al. (2023). A Robo-hand prototype design gripping device within the framework of sustainable development. Indian Journal of Engineering, 20, e37ije1673.

32. Abu-Jassar, A. T., Attar, H., Lyashenko, V., Amer, A., Sotnik, S., & Solyman, A. (2023). Access control to robotic systems based on biometric: the generalized model and its practical implementation. International Journal of Intelligent Engineering and Systems, 16(5), 313-328.

33. Al-Sharo, Y. M., Abu-Jassar, A. T., Sotnik, S., & Lyashenko, V. (2023). Generalized Procedure for Determining the Collision-Free Trajectory for a Robotic Arm. Tikrit Journal of Engineering Sciences, 30(2), 142-151.

34. Lyashenko, V., Abu-Jassar, A. T., Yevsieiev, V., & Maksymova, S. (2023). Automated Monitoring and Visualization System in Production. International Research Journal of Multidisciplinary Technovation, 5(6), 9-18.

35. Kuzemin, A., & Lyashenko, V. (2008). Conceptual Foundations of Construction of the Models and Procedures for Prediction of the Avalanche-dangerous Situations Initiation. International Journal INFORMATION THEORIES & APPLICATIONS, 15(2), 153-158.

36. Kuzomin, O., Lyashenko, V., Dudka, O., Radchenko, V., & Vasylenko, O. (2020). Using of ontologies for building databases and knowledge bases for consequences management of

emergency. International Journal of Advanced Trends in Computer Science and Engineering, 9(4), 5040-5045.

37. Zeleniy, O., Rudenko, D., Lyubchenko, V., & Lyashenko, V. (2022). Image Processing as an Analysis Tool in Medical Research. Image, 6(9), 135-141.

38. Abu-Jassar, A. T., Attar, H., Amer, A., Lyashenko, V., Yevsieiev, V., & Solyman, A. (2024). Remote Monitoring System of Patient Status in Social IoT Environments Using Amazon Web Services (AWS) Technologies and Smart Health Care. International Journal of Crowd Science.

39. Abu-Jassar, A. T., Attar, H., Amer, A., Lyashenko, V., Yevsieiev, V., & Solyman, A. (2024). Development and Investigation of Vision System for a Small-Sized Mobile Humanoid Robot in a Smart Environment. International Journal of Crowd Science.

40. Lyubchenko, V., Veretelnyk, K., Kots, P., & Lyashenko, V. (2024). Digital image segmentation procedure as an example of an NP-problem. Multidisciplinary Journal of Science and Technology, 4(4), 170-177.

41. Bai, Q., & et al. (2020). Object detection recognition and robot grasping based on machine learning: A survey. IEEE access, 8, 181855-181879.

42. Li, G., & et al. (2020). Skin-inspired quadruple tactile sensors integrated on a robot hand enable object recognition. Science Robotics, 5(49), eabc8134.

43. Li, N., & et al. (2022). A triboelectric-inductive hybrid tactile sensor for highly accurate object recognition. Nano Energy, 96, 107063.

44. Song, Q., & et al. (2021). Object detection method for grasping robot based on improved YOLOv5. Micromachines, 12(11), 1273.

45. Koskinopoulou, M., & et al. (2021). Robotic waste sorting technology: Toward a vision-based categorization system for the industrial robotic separation of recyclable waste. IEEE Robotics & Automation Magazine, 28(2), 50-60.

46. Fan, J., & et al. (2022). Vision-based holistic scene understanding towards proactive human–robot collaboration. Robotics and Computer-Integrated Manufacturing, 75, 102304.