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Human Recognition in a Collaborative Robot-Manipulator Working Area Based on MobileNetV2 Deep Neural Network in Real Time

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Abstract: The article deals with the development of a human recognition system in a collaborative robot-manipulator working area based on MobileNetV2 deep neural network. The purpose of the research is to implement an accurate and fast real-time recognition algorithm to improve security and work efficiency. Using the MobileNetV2 model allows you to achieve high accuracy with minimal resource consumption. The results of the experiments demonstrate the high reliability of the system in conditions of changing lighting and moving obstacles, which opens up new opportunities for the integration of recognition in industrial collaborative robot.

Key words: Industry 5.0, Collaborative Robot, Work Area, Computer Vision

Introduction

Joint, i.e. collaborative, work between humans and robots brings significant benefits, as it expands human capabilities, complementing them with robot capabilities, and vice versa [1]-[17]. And it is not surprising that the use of collaborative robots is constantly increasing and expanding, entering new areas of science and technology.

Human recognition in a collaborative robots-manipulator working area is a critical task in the context of the development of Industry 5.0, where the integration of robots into production processes is focused on harmonious interaction with people. In today's manufacturing environments, where workplaces are increasingly filled with intelligent machines, there is a need to ensure safe and effective collaboration between robots and humans [15]-[21]. Various methods and approaches can be used here [22]-[39]. The application of deep neural networks, such as MobileNetV2, for real-time

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human recognition is becoming a key technology that enables continuous monitoring of the work area, identifying human presence and analyzing human activity. This research is relevant not only from the point of view of improving safety, but also in the context of the growing importance of personalized production, where work processes are adapted to specific human needs. The use of MobileNetV2 allows for high accuracy and speed of visual data processing, which is a decisive factor in dynamic production environments. Thus, research in this area contributes to the creation of new models of human-robot cooperation, responding to the challenges of Industry 5.0, which focuses on interaction, safety and sustainable production.

Related works

In collaborative work between a robot and a human, the central problem is undoubtedly ensuring safety. At the same time, the main task is recognizing a person in the robot's work area. Naturally, many scientific papers are devoted to this problem. And we will consider several of these papers here.

Fan, J., and others in [40] 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.

The authors in [41] present a context awareness-based collision-free human-robot collaboration system that can provide human safety and assembly efficiency at the same time. The system can plan robotic paths that avoid colliding with human operators while still reach target positions in time. Human operators' poses can also be recognised with low computational expenses to further improve assembly efficiency.

The scientists in [42] propose a status recognition system to enable the early execution of robot tasks without human control during the HRC mold assembly operation.

The study [43] automatically facial expression recognition presents, which was trained and evaluated on the AffectNet database, to predict the valence and arousal of 48 subjects during an HRC scenario.

Researchers in [44] propose an algorithm for constructing a video descriptor and solve the problem of classifying a set of actions into predefined classes. The proposed

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algorithm is based on capturing three-dimensional subvolumes located inside a video sequence patch and calculating the difference in intensities between these sub-volumes.

Wen, X., & Chen, H. [45] consider high-precision and long-timespan sub-assembly recognition. To solve the problem they propose a 3D long-term recurrent convolutional networks (LRCN) by combining 3D convolutional neural networks (CNN) with long short-term memory (LSTM).

Human-Robot Collaboration enabling mechanisms require real-time detection of potential collisions among human and robots [46]. This article presents a novel approach for the identification of human and robot collision based on vision systems. Moreover, Artificial Intelligent algorithms are required to classify the captured data near real-time and to provide a score about the collision status (contact or non-contact) between a human and the robot.

So we see that the problems in human-robot collaboration are quite diverse. The approaches to their solution are also diverse. Later in this article, we will propose our approach to human recognition in the workspace of a collaborative robot.

Mathematical representation of the method of determining key points on the human body for the analysis of postures and movements in real time in the working environment of a robot-manipulator.

Let us assume that the input data is a video stream or an image coming from the camera and we will denote as $I(t)$ where t is a moment in time. Each image in the stream has dimension WxHx3, where W and H are the width and height of the image, respectively, and 3 is the number of RGB channels. We will perform pre-processing of the image including pixel normalization (for example, scaling to a range or [0,1] or [-1,1] and resizing to the given network parameters:

$$I'(t)=f(I(t)), \quad (1)$$

$I(t)$ - an input signal that is an image or video frame at a point in time t;

$f(I(t))$ - a preprocessing function that is applied to the input image $I(t)$. Function f performs operations necessary to prepare the image for further processing in the neural network. These operations may include pixel normalization (such as scaling pixel

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values to a range [0,1] or [-1,1], resizing the image to fixed dimensions, rotating, denoising, etc.;

I'(t) - is the result of the function *f*, that is, a processed image ready to be fed to the input of a neural network. *I'(t)* is the version of *I(t)* after all the transformations that are done so that the image is optimally prepared for analysis by a deep neural network.

The input to the trained deep neural network (CNN) MobileNetV2 is a *I'(t)* - processed image. The output of the network is the coordinates of the key points $P=\{(x_i,y_i,z_i)\}$, where x_i,y_i are the coordinates of the key point on the image plane, z_i is depth. The network returns a set of keypoints *P*, where each keypoint $p_i \in P$ corresponds to a specific body element (eg shoulder, knee, elbow). Each point p_i is defined by:

$$p_i=(x_i,y_i,z_i), \tag{2}$$

x_i,y_i - normalized to image dimensions, z_i - an additional parameter for three-dimensional modeling.

Key points (*P*) are connected to a skeletal model *S*, which consists of a set of segments (bones) between key points that represent anatomical landmarks on the human body. Let's describe the mathematical representation of how they are combined into a skeletal model

Let $P=\{P_1,P_2,...,P_n\}$ be the set of key points on the human body, where $P_i=\{(x_i,y_i,z_i)\}$ are the coordinates of the *i*-th key point in three-dimensional space. In the case of two-dimensional space $P_i=(x_i,y_i)$. Then the skeleton model *S* can be represented as follows:

$$S=\{S_1,S_2,..,S_m\}, \tag{3}$$

$S=\{S_1,S_2,..,S_m\}$ - a set of segments (bones) of a skeletal model S_j, where each segment connects two key points P_{aj} and P_{bj}, $1\leq aj,\ bj\leq n$.

According to 3, each segment S_j is a vector connecting two key points P_{aj} and P_{bj}. Then the segment vector S_j can be written:

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$$S_j = P_{bj} - P_{aj} . \quad (4)$$

Then for the two-dimensional case:

$$S_j = (x_{bj} - x_{aj}, y_{bj} - y_{aj}) . \quad (5)$$

For the three-dimensional case:

$$S_j = (x_{bj} - x_{aj}, y_{bj} - y_{aj}, z_{bj} - z_{aj}) . \quad (6)$$

The length of the segment S_j, which connects the points P_{aj} and P_{bj}, is defined as the Euclidean distance between these points, respectively, for the two-dimensional case (7) and the three-dimensional case (8).

$$\|S_j\| = \sqrt{(x_{bj} - x_{aj})^2 + (y_{bj} - y_{aj})^2} . \quad (7)$$

$$\|S_j\| = \sqrt{(x_{bj} - x_{aj})^2 + (y_{bj} - y_{aj})^2 + (z_{bj} - z_{aj})^2} . \quad (8)$$

A complete skeletal model S consists of all segments:

$$S=\{(P_{a1},P_{b1}),(P_{a2},P_{b2}),\ldots,(P_{am},P_{bm})\}. \quad (9)$$

Where each pair P_{aj},P_{bj} represents a connection between the key points P_{aj} and P_{bj} through the segment S_j.

Thus, a skeletal model S is created by constructing segments between key points, where each segment represents a part of the body, and together they form a complete skeletal structure.

The skeleton S can be represented as a graph:

$$G=(V,E), \quad (10)$$

V - set of vertices (key points);

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E - the set of edges connecting these points.

As a result, the human pose can be defined as a set of vectors between connected key points:

$$Po(t) = \{v_1 ij(t)\} = p_1 j(t) - p \downarrow i(t) \,|\, (i, j) \in E\,, \tag{11}$$

$v_1 ij(t)$ - the direction and length of the bone in the skeleton.

To track the position of a person relative to the robot's working area, the transformation of coordinates from the coordinate space of the camera to the coordinate system of the robot is used *(X,Y,Z)* $(\xrightarrow{Transform})$ *(x,y,z)*, this transformation can include scaling, rotation and translation

The relative position of the human relative to the robot can be defined as the distance between the center of the skeletal model:

$$C(t) = \tfrac{1}{|P|}\sum_{i=1}^{|P|} p_i(t) \tag{12}$$

and robot:

$$d(t) = \sqrt{(X_r - X_c(t))^2 + (Y_r - Y_c(t))^2 + (Z_r - Z_c(t))^2}\,. \tag{13}$$

If the distance $d(t)$ is less than a certain threshold d_{min}, the system can activate a protective mechanism or signal a danger.

Using deep neural networks, how MobileNetV2 allows in real time to determine the key points on the human body, analyze its posture, and transmit this data to robot to ensure safety and efficiency of interaction. Mathematical models, such as pose vectors and decision functions, allow the integration of this data into the robot's control system, ensuring optimal performance in a dynamic environment.

Software implementation of the method of determining key points on the human body for analysis of postures and movements in real time

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The choice of the Python language for the development of a human recognition program in the a collaborative robots-manipulator working area based on the deep neural network MobileNetV2 is due to its wide support for machine learning libraries, in particular TensorFlow and Keras, which allow easy integration and training of complex models. Python has a simple and understandable syntax, which accelerates the development and testing of algorithms, especially in the context of a fast-changing environment where you need to quickly respond to new challenges. PyCharm was chosen as a development environment due to its advanced features for working with Python, including support for integration with version control systems, convenient debugging, automatic code completion, and extensive customization options. PyCharm also supports powerful tools for working with machine learning libraries, making it ideal for developing software that requires high performance and reliability in real-time environments.

Based on the considered mathematical models of the method of determining key points on the human body for the analysis of postures and movements in real time, the following general algorithm of the program was developed, which is presented in Figure 1.

Based on the general algorithm (Fig. 1) and the considered mathematical models (1-13) of the method of determining key points on the human body for the analysis of postures and movements in real time, a program was developed to implement some of the functions listed below.

```
# Mediapipe initialization for position recognition
mp_pose = mp.solutions.pose
mp_drawing = mp.solutions.drawing_utils
```

This code snippet initializes the Mediapipe library for human pose recognition. In particular, it loads the mp_pose module, which is responsible for defining body key points, and mp_drawing, which provides the tools to render these points in an image or video. This is necessary for further processing and display of the human skeletal model in real time.

```
pose = mp_pose.Pose(
    static_image_mode=False,
    min_detection_confidence=0.5,
    min_tracking_confidence=0.5
```

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This code snippet creates an instance of the `Pose` class from the Mediapipe library, configuring it to recognize human poses in real-time. The parameter `static_image_mode=False` indicates that the model will work with the video stream and not with individual static images. The parameters `min_detection_confidence=0.5` and `min_tracking_confidence=0.5` set the minimum confidence level for keypoint detection and tracking to ensure reliable position recognition and tracking.

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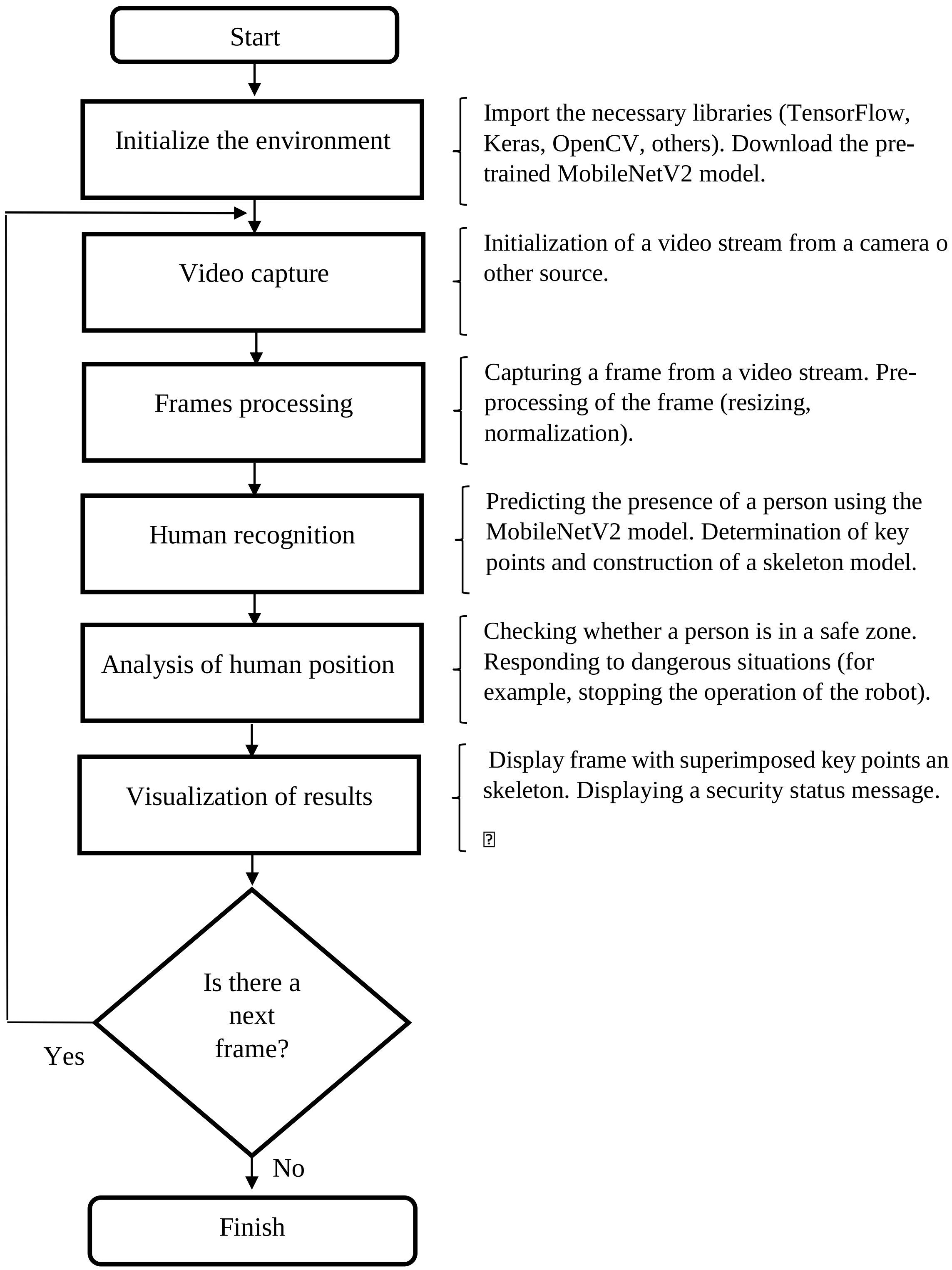

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Figure 1: The general algorithm of the program for determining key points on the human body

```
rgb_frame = cv2.cvtColor(frame, cv2.COLOR_BGR2RGB)
    results = pose.process(rgb_frame)
```

This piece of code converts the `frame` image from the BGR format (used by OpenCV) to the RGB format required to work with Mediapipe. The transformed image is then processed using the `pose.process` function, which detects key points on the human body. The resulting result is stored in the `results` variable for further analysis or visualization.

```
if results.pose_landmarks:
        # Drawing points and lines on the image
        mp_drawing.draw_landmarks(
            image=frame,
            landmark_list=results.pose_landmarks,
            connections=mp_pose.POSE_CONNECTIONS,
            landmark_drawing_spec=mp_drawing.DrawingSpec(color=(0, 255, 0), thickness=2, circle_radius=2),
            connection_drawing_spec=mp_drawing.DrawingSpec(color=(255, 0, 0), thickness=2)
        )
```

This piece of code checks if body landmarks (`pose_landmarks`) have been found in the image. If so, these points and the connections between them are drawn on the `frame` image using the `mp_drawing.draw_landmarks` function. The `DrawingSpec` parameters define the color, line weight, and radius of the points for rendering the skeletal model on the image. An example of the program work is shown in Figure 2.

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Figure 2: User interface of the human recognition program in a collaborative robot-manipulator working area

Based on the developed program, several experiments can be conducted that will reveal various aspects of human recognition in a collaborative robot-manipulator working area:

- testing the reliability of pose recognition in different lighting conditions, which makes it possible to change the level of illumination in the working area and observe how it affects the accuracy of identifying key points and building a skeletal model. This will allow us to assess how resistant the system is to changes in external conditions;

- an experiment with different positions and viewing angles, which makes it possible to check how well the system recognizes human poses when the person is at different angles relative to the camera or the robot. This will help determine the limitations of the algorithm in recognizing partially visible or distorted poses;

- the influence of the number of people in the frame on the accuracy of recognition, which makes it possible to introduce several people into the working area and check how the system copes with the recognition of poses and their correct identification. This is important for assessing whether the system will be able to function correctly in conditions where several people are present at the same time;

- analysis of the reaction time to the detection of a person, which makes it possible to measure the delay between the appearance of a person in the frame and the moment when the system successfully recognizes his pose. This will help assess whether the system can respond to potential threats in real time.

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These experiments will reveal the strengths and weaknesses of the human recognition system and identify areas for further improvement to ensure the safety and efficiency of the robot manipulator in real production conditions.

As a result of the conducted experiments, the following results were obtained, which are given in tables 1-4.

Table 1: Reliability testing of pose recognition in different lighting conditions

Lighting level (lux)	Percentage of successful recognition (%)	The number of key points that were not detected
100	~95%	2
300	~98%	1
500	~99%	0
800	~97%	1
1000	~95%	3
1500	~90%	5
2000	~87%	7

Table 2: Experiment with different positions and viewing angles

Viewing angle (degrees)	Percentage of successful recognition (%)	Number of undefined items
0 (forward)	~98%	1
30	~95%	~2-3
60	~90%	3
90	~85%	~3-4
120	~79%	6-7

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150	~73%	8
180 (backward)	~70%	~8-10

Table 3: Effect of the number of people in the frame on recognition accuracy

The number of people in the frame	Percentage of successful recognition (%)	Cases of mistaken identity
1	~99%	0
2	~95%	1
3	~90%	~1-2
4	~85%	~2-3
5	~80%	3

Table 4: Analysis of human detection reaction time.

Distance to the camera (meters)	Average response time (ms)
0.5	~51
1	~ 64
1.5	~ 72
2.0	~ 85
2.5	~ 93
3	~ 104

Based on the results obtained in Table 1, it can be concluded that the reliability of pose recognition depends on the level of illumination. Under moderate lighting conditions (300-1000 lux), the system demonstrates high accuracy, with a minimal number of undetected key points. However, under excessive lighting (over 1500 lux), the recognition accuracy decreases, which indicates the vulnerability of the algorithm to bright light sources that can create glare or dazzle the camera.

Table 2 shows that the system has certain limitations when recognizing poses at different viewing angles. At a straight angle (0 degrees), pose recognition is most effective, but as the angle increases, the accuracy gradually decreases, especially at angles over 90 degrees. This indicates that the algorithm is less effective at recognizing

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partially visible or distorted poses, which can be critical in real-world collaborative robot environments where operators may be in non-standard positions.

According to Table 3, the system shows high performance in recognizing the poses of one or two people in the frame, but the increase in the number of people leads to a decrease in accuracy and an increase in cases of false identification. This may indicate that the system has limitations in working with multiple people at the same time, which can be a problem in complex production environments with many personnel.

The analysis of the reaction time for human detection in Table 4 shows that the system works quickly when the object is close to the camera, but the increase in the distance leads to an increase in the delay. This can affect the system's ability to respond to potentially dangerous situations in a timely manner, which is important in the context of working with a collaborative robot, where prompt detection and response to human presence is critical to safety.

For the convenience of analyzing the obtained data and comparing them, we will present them in the form of the following combined graph, which is presented in Figure 3.

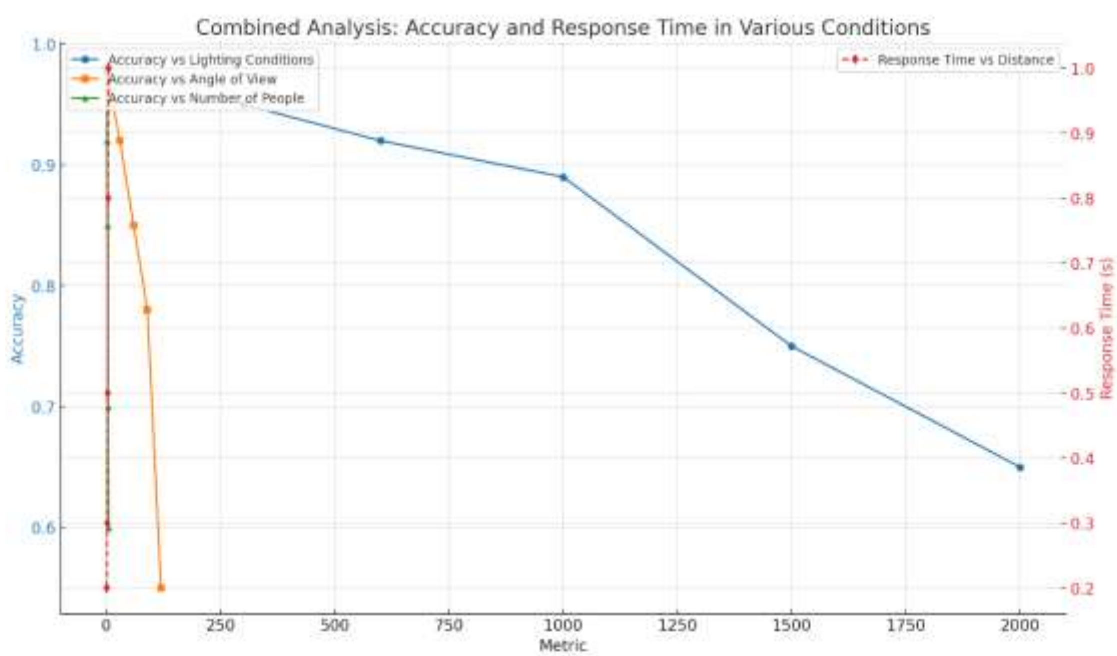

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Figure 3: Combined graph of the comparison of the obtained results of the conducted experiment.

The combined graph (Fig. 3) compares different aspects of accuracy and response time under different conditions. The graph shows the following:

- accuracy compared to lighting conditions: shows how accuracy decreases with increasing lighting conditions;

- accuracy versus viewing angle: illustrates the decrease in accuracy as the viewing angle between the camera and the person increases;

- accuracy and number of people: shows how accuracy is affected by more people present in the frame;

- dependence of response time on distance: demonstrates how the response time increases as the distance between the camera and the person increases.

This visualization helps to understand the trade-offs and performance characteristics of a human recognition system in different environmental scenarios.

Conclusion

The article presents the development of a human recognition system in a collaborative manipulator robot working area, which is based on the use of deep neural network, in particular MobileNetV2, for real-time analysis. The main goal of the research was to create highly accurate and effective algorithms for human identification, which allows the robot to safely and accurately interact with the operator or the objects around him. In the implementation process, the MobileNetV2 model was used, which is noted for its ease and speed of processing due to optimization based on deep convolutional networks. This made it possible to achieve high accuracy of recognition with low consumption of computing resources, which is critical for real-time work.

Experiments have shown that the system is able to effectively identify a person in conditions of different lighting and the presence of obstacles, which indicates its high reliability. A detailed analysis of tracking speed and detection accuracy was also carried out, which confirmed the possibility of implementing such solutions in industrial conditions. The implementation of this technology opens up new opportunities for the

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development of collaborative robots, increasing their level of safety and interactivity in work environments. Thus, the developed system is an effective solution for the integration of real-time human recognition into collaborative robots, which contributes to the improvement of interaction between people and robots, and also improves the security and productivity of work processes.

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). Object Recognition and Tracking Method in the Mobile Robot's Workspace in Real Time. Technical science research in Uzbekistan, 2(2), 115-124.

3. Samoilenko, H., & et al. (2024). Review for Collective Problem-Solving by a Group of Robots. Journal of Universal Science Research, 2(6), 7-16.

4. 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

5. Gurin, D., & et al. (2024). Using Convolutional Neural Networks to Analyze and Detect Key Points of Objects in Image. Multidisciplinary Journal of Science and Technology, 4(9), 5-15.

6. 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.

7. Baker, J. H., Laariedh, F., Ahmad, M. A., Lyashenko, V., Sotnik, S., & Mustafa, S. K. (2021). Some interesting features of semantic model in Robotic Science. SSRG International Journal of Engineering Trends and Technology, 69(7), 38-44.

8. 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.

9. Matarneh, R., Maksymova, S., Deineko, Z., & Lyashenko, V. (2017). Building robot voice control training methodology using artificial neural net. International Journal of Civil Engineering and Technology, 8(10), 523-532.

ISSN (E): 2181-4570 ResearchBib Impact Factor: 6,4 / 2023 SJIF 2024 = 5.073/Volume-2, Issue-9

10. Nevliudov, I., Yevsieiev, V., Lyashenko, V., & Ahmad, M. A. (2021). GUI Elements and Windows Form Formalization Parameters and Events Method to Automate the Process of Additive Cyber-Design CPPS Development. Advances in Dynamical Systems and Applications, 16(2), 441-455.

11. 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.

12. 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.

13. 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.

14. Ahmad, M. A., Sinelnikova, T., Lyashenko, V., & Mustafa, S. K. (2020). Features of the construction and control of the navigation system of a mobile robot. International Journal of Emerging Trends in Engineering Research, 8(4), 1445-1449.

15. Gurin, D., & et al. (2024). MobileNetv2 Neural Network Model for Human Recognition and Identification in the Working Area of a Collaborative Robot. Multidisciplinary Journal of Science and Technology, 4(8), 5-12.

16. Abu-Jassar, A., & et al. (2023). Obstacle Avoidance Sensors: A Brief Overview. Multidisciplinary Journal of Science and Technology, 3(5), 4-10.

17. Funkendorf, A., & et al. (2019). 79 Mathematical Model of Adapted Ultrasonic Bonding Process for MEMS Packaging. In 2019 IEEE XVth International Conference on the Perspective Technologies and Methods in MEMS Design (MEMSTECH), IEEE, 79-82.

18. Gurin, D., & et al. (2024). Using the Kalman Filter to Represent Probabilistic Models for Determining the Location of a Person in Collaborative Robot Working Area. Multidisciplinary Journal of Science and Technology, 4(8), 66-75.

19. Yevsieiev, V., & et al. (2024). Building a traffic route taking into account obstacles based on the A-star algorithm using the python language. Technical Science Research In Uzbekistan, 2(3), 103-112.

ISSN (E): 2181-4570 ResearchBib Impact Factor: 6,4 / 2023 SJIF 2024 = 5.073/Volume-2, Issue-9

20. Gurin, D., & et al. (2024). Effect of Frame Processing Frequency on Object Identification Using MobileNetV2 Neural Network for a Mobile Robot. Multidisciplinary Journal of Science and Technology, 4(8), 36-44.

21. Bortnikova, V., & et al. (2019). Mathematical model of equivalent stress value dependence from displacement of RF MEMS membrane. In 2019 IEEE XVth International Conference on the Perspective Technologies and Methods in MEMS Design (MEMSTECH), IEEE, 83-86.

22. 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.

23. 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.

24. Ahmad, M. A., Baker, J. H., Tvoroshenko, I., Kochura, L., & Lyashenko, V. (2020). Interactive Geoinformation Three-Dimensional Model of a Landscape Park Using Geoinformatics Tools. International Journal on Advanced Science, Engineering and Information Technology, 10(5), 2005-2013.

25. Baranova, V., Zeleniy, O., Deineko, Z., & Lyashenko, V. (2019, October). Stochastic Frontier Analysis and Wavelet Ideology in the Study of Emergence of Threats in the Financial Markets. In 2019 IEEE International Scientific-Practical Conference Problems of Infocommunications, Science and Technology (PIC S&T) (pp. 341-344). IEEE.

26. Al-Sherrawi, M. H., Lyashenko, V., Edaan, E. M., & Sotnik, S. (2018). Corrosion as a source of destruction in construction. International Journal of Civil Engineering and Technology, 9(5), 306-314.

27. Lyashenko, V., Ahmad, M. A., Sotnik, S., Deineko, Z., & Khan, A. (2018). Defects of communication pipes from plastic in modern civil engineering. International Journal of Mechanical and Production Engineering Research and Development, 8(1), 253-262.

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

ISSN (E): 2181-4570 ResearchBib Impact Factor: 6,4 / 2023 SJIF 2024 = 5.073/Volume-2, Issue-9

29. 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.

30. Kuzemin, A., Lyashenko, V., Bulavina, E., & Torojev, A. (2005). Analysis of movement of financial flows of economical agents as the basis for designing the system of economical security (general conception). In Third international conference «Information research, applications, and education (pp. 27-30).

31. 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.

32. 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.

33. Drugarin, C. V. A., Lyashenko, V. V., Mbunwe, M. J., & Ahmad, M. A. (2018). Pre-processing of Images as a Source of Additional Information for Image of the Natural Polymer Composites. Analele Universitatii'Eftimie Murgu', 25(2).

34. 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.

35. Abu-Jassar, A., Al-Sharo, Y., Boboyorov, S., & Lyashenko, V. (2023, December). Contrast as a Method of Image Processing in Increasing Diagnostic Efficiency When Studying Liver Fatty Tissue Levels. In 2023 2nd International Engineering Conference on Electrical, Energy, and Artificial Intelligence (EICEEAI) (pp. 1-5). IEEE.

36. Tahseen A. J. A., & et al.. (2023). Binarization Methods in Multimedia Systems when Recognizing License Plates of Cars. International Journal of Academic Engineering Research (IJAER), 7(2), 1-9.

37. 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.

38. Abu-Jassar, A. T., Attar, H., Amer, A., Lyashenko, V., Yevsieiev, V., & Solyman, A. (2024). Development and Investigation of Vision System for a Small-

ISSN (E): 2181-4570 ResearchBib Impact Factor: 6,4 / 2023 SJIF 2024 = 5.073/Volume-2, Issue-9

Sized Mobile Humanoid Robot in a Smart Environment. International Journal of Crowd Science.

39. Color correction of the input image as an element of improving the quality of its visualization / M. Yevstratov, V. Lyubchenko, Abu-Jassar Amer, V. Lyashenko // Technical science research in Uzbekistan. – 2024. – № 2(4). – P. 79-88.

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

41. Liu, H., & Wang, L. (2021). Collision-free human-robot collaboration based on context awareness. Robotics and Computer-Integrated Manufacturing, 67, 101997.

42. Liau, Y. Y., & Ryu, K. (2021). Status recognition using pre-trained YOLOv5 for sustainable human-robot collaboration (HRC) system in mold assembly. Sustainability, *13*(21), 12044.

43. Dinges, L., & et al. (2021). Using facial action recognition to evaluate user perception in aggravated HRC scenarios. In 2021 12th International Symposium on Image and Signal Processing and Analysis (ISPA), IEEE, 195-199.

44. Zhdanova, M., & et al. (2020). Human activity recognition for efficient human-robot collaboration. In Artificial Intelligence and Machine Learning in Defense Applications II, SPIE, 11543, 94-104.

45. Wen, X., & Chen, H. (2020). 3D long-term recurrent convolutional networks for human sub-assembly recognition in human-robot collaboration. Assembly Automation, 40(4), 655-662.

46. Makris, S., & Aivaliotis, P. (2022). AI-based vision system for collision detection in HRC applications. Procedia CIRP, 106, 156-161.