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MobileNetv2 Neural Network Model for Human Recognition and Identification in the Working Area of a Collaborative Robot

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Abstract: The article considers the software implementation of the MobileNetV2 neural network model for human recognition and identification in the working area of a collaborative robot. A mathematical description of the MobileNetV2 operation is presented, in particular its architecture and principles of operation, which allow to achieve high accuracy with reduced computing costs. The process of implementing the model in Python using the PyCharm environment is described, and a number of tests were conducted to evaluate its effectiveness in real-time conditions. The test results demonstrate the high accuracy and speed of the model, which confirms its suitability for use in collaborative robot systems that interact with people.

Key words: Industry 5.0, Collaborative Robots, Work Area, Computer Vision, Identification

Introduction

The use of not one robot, but several, especially with the participation of a person in the performance of the task, leads to the emergence of a number of challenges [1]-[6]. Collaborative robots are robots that work in connection with a person. Part of the work can be done by them, and the other part by a person. But the presence of a person leads to the emergence of a subjective factor that cannot be predicted and programmed. Here is added the task of necessarily "seeing" your environment, seeing objects in it, especially a person in the robot's working area [7]-[16]. Various methods and approaches can be used for this [17]-[41].

The relevance of research in the field of software implementation of the MobileNetV2 neural network model for human recognition and identification in the working area of a collaborative robot is growing in the conditions of rapid production processes automation and robotization development. Collaborative robots that work alongside humans require a high level of accuracy in detecting and identifying a person to ensure the safety and efficiency of their interaction with a human operator. The MobileNetV2 model, due to its compactness and efficiency, is an ideal candidate for such tasks, as it provides high recognition quality with reduced computational costs. In the context of increasing productivity and reducing the cost of computing resources, the implementation of such systems is not only relevant, but also necessary for implementation in real conditions. The study and optimization of these models allow to increase the safety and efficiency of the work of collaborative robots, which is an important step for the integration of advanced technologies within the framework of Industry 5.0 concepts.

Related works

Many scientific papers are devoted to the problem of finding objects, as well as a person, in the robot's workspace. Let us consider several recent works on this topic.

Bonci, A., and co-authors in [42] note that perception capability assumes significant importance for human–robot interaction. If the robot is not aware of the human position and intention, a shared workspace between robots and humans may decrease productivity and lead to human safety issues. They present a survey on sensory equipment useful for human detection and action recognition in industrial environments.

The study [43] presents a framework for ensuring human safety in a robotic cell that allows human–robot coexistence and dependable interaction. The framework is based on a layered control architecture that exploits an effective algorithm for online monitoring of relative human–robot distance using depth sensors.

The authors in [44] propose their robotic pick-and-place system that is capable of grasping and recognizing both known and novel objects in cluttered environments. The key new feature of the system is that it handles a wide range of object categories without needing any task-specific training data for novel objects.

An approach for safe, and object-independent human-to-robot handovers using real time robotic vision, and manipulation is presented in [45]. Putting a high emphasis on safety, two perception modules are used: human body part segmentation, and hand/finger segmentation.

Intelligent planning and control algorithms are needed for the organization of the work in hybrid teams of humans and robots [46]. This paper [46] introduces an approach to use standardized work description for automated procedure generation of mobile assistant robots.

Mathematical representation of the MobileNetV2 neural network for human recognition and identification in the working area of a collaborative robot

The MobileNetV2 neural network model is one of the effective models for recognizing and identifying objects, including people, in the working area of a collaborative robot.

The architecture of the MobileNetV2 model neural network can be described by the following mathematical expressions.

– input data passes through a convolutional layer, which calculates activations using convolutional kernels (filters). Mathematically, this is described as:

$$y = f(W \times x + b) \tag{1}$$

W – convolutional core (weights);

x – input tensor;

b – bias;

f – activation function.

– deep convolution applies convolutional kernels separately to each channel of the input image:

$$y_{k,l} = \sum_{i,j} K_{i,j} \cdot x_{k+i,l+j} \tag{2}$$

$K_{i,j}$ – convolutional core;

x – input tensor;

y – output tensor.

– pointwise convolution uses 1×1 convolutions for mixing channels:

$$y_{k,l,m} = \sum_{n} W_{l,1,n,m} \cdot x_{k,l,n} \tag{3}$$

W – point collapse scales;

x – input tensor;

y – output tensor.

– the basic structure of MobileNetV2 consists of blocks of inverted residuals, which use narrowing and expanding for efficient calculation:

$$y = x + F(x, W) \tag{4}$$

F – a non-linear transformation involving convolutional layers;

W – appropriate weights.

– on the last layers, linear activation is used instead of non-linear to avoid information loss:

$$y = W_{1\times 1} \cdot ReLU(W_{3\times 3} \cdot x) \tag{5}$$

$W_{1\times 1}$ and $W_{3\times 3}$ – convolutional nuclei;

$ReLU$ – non-linear activation.

Software implementation of the MobileNetV2 neural network for human recognition and identification in the working area of a collaborative robot in Python

The choice of the Python language for the implementation of the MobileNetV2 neural network model is due to its wide capabilities in the field of machine learning and data processing. Python has a rich set of libraries and frameworks, such as TensorFlow and Keras, that provide a convenient interface for working with and training neural networks. In addition, Python has a simple syntax and supports integration with other tools, making it an ideal choice for developing and implementing real-time object recognition and identification. Given these advantages, Python facilitates the efficient development and testing of complex algorithms for collaborative robots.

We will give an example of the software implementation of the developed human recognition and identification program in the working area of a collaborative robot in the Python language.

The choice of the Python language has wide capabilities in the field of machine learning and data processing. Python has a rich set of libraries and frameworks such as.

```
import cv2
import numpy as np
import tensorflow as tf
```

Allows you to import libraries necessary for image processing, numerical calculations and work with neural networks. cv2 provides functions for image and video processing, numpy provides capabilities for working with numeric arrays, and tensorflow provides tools for building and training neural Network

```
model = tf.saved_model.load(r"C:\Users\Vladyslav\.cache\kagglehub\models\ tensorflow\ssd-mobilenet-v2\tensorFlow2\fpnlite-320x320\1")
```

Allows you to load a saved TensorFlow model from the specified path. This allows the already trained model to be used for further prediction or estimation without the need for retraining.

```
# Function for recognizing objects in the image
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 detect_objects function is designed to recognize objects in an image. It converts the image to a TensorFlow tensor, adds a new dimension to the batch, and passes this tensor to the model to perform prediction. The returned detections contain information about detected objects in the image. An example of a software implementation of the MobileNetV2 neural network for human recognition and identification in the working area of a collaborative robot in Python is shown in Figure 1.

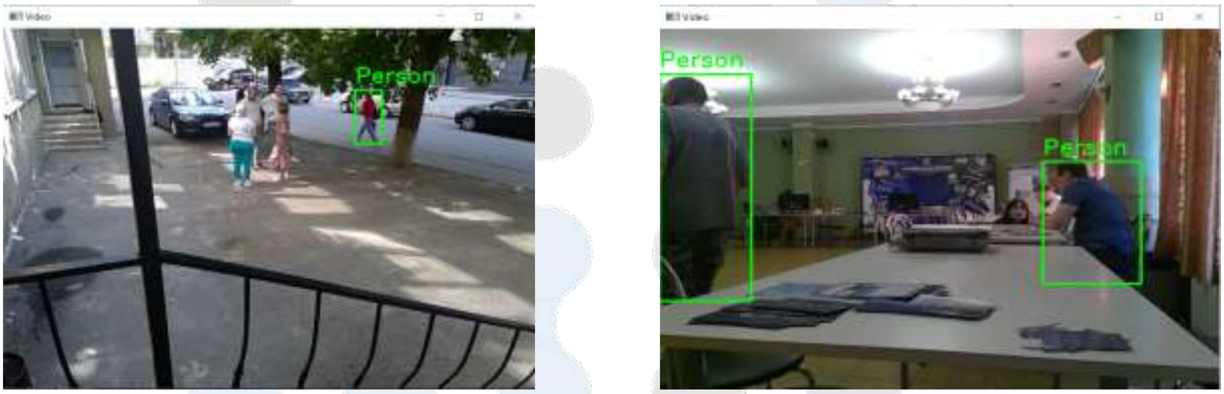

Figure 1: An example of software implementation of the MobileNetV2 neural network for human recognition and identification in the working area of a collaborative robot

Based on the developed program, we will test the accuracy of recognition of the developed human identification system in the working area of the collaborative robot, the results of which are presented in Table 1, and the visualization of the obtained data is presented in Figure 2.

Table 1: Obtained results of testing the recognition accuracy of the developed human identification system in the working area of the collaborative robot.

Test script	Number of images	Number of correct identifications	Number of false identifications	Accuracy (%)
Scenario 1: Different angles	100	92	8	92.0
Scenario 2: Different lighting	100	85	15	85.0
Scenario 3: Interaction with other objects	100	88	12	88.0
Scenario 4: Dynamic movements	100	90	10	90.0
Scenario 5: Different distances	100	87	13	87.0

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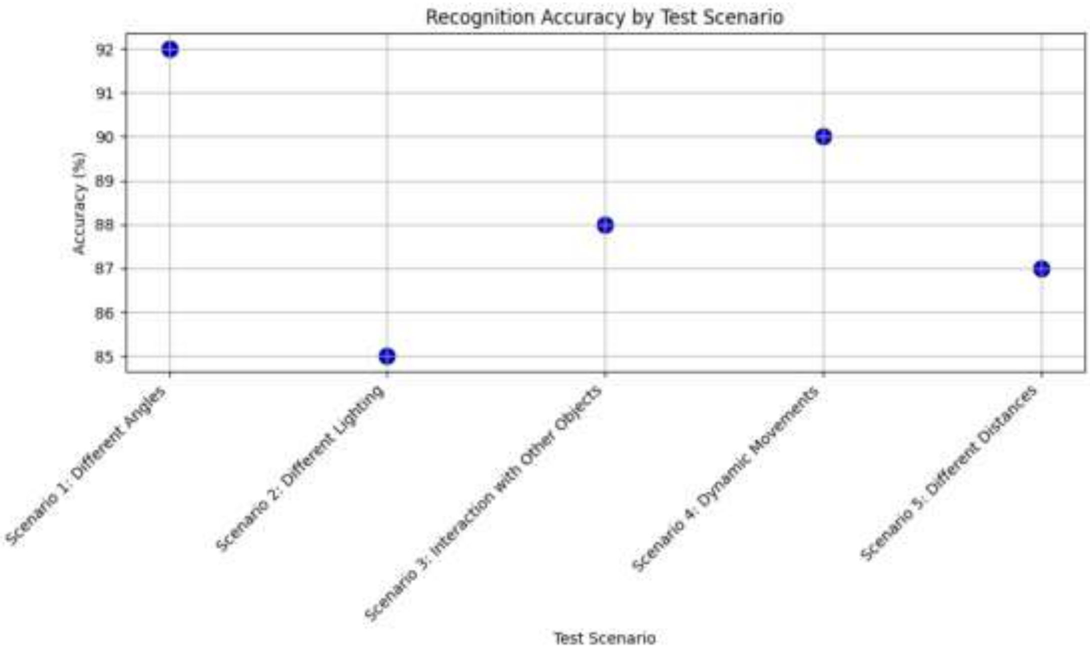

Figure 2: Graph of the obtained results of testing the recognition accuracy of the developed human identification system in the working area of the collaborative robot.

The general conclusions from the data table obtained during the testing of the recognition accuracy of the human identification system in the working area of the collaborative robot testify to the high efficiency of the model in various conditions. The highest accuracy was achieved in the scenario "Different angles" (92%), which confirms the stability of the model at different viewing angles. In the "Different lighting" scenario, accuracy dropped to 85%, indicating the effect of lighting on recognition quality. Test results for "Interaction with other objects" and "Dynamic movements" showed an accuracy of 88% and 90%, respectively, which demonstrates the good adaptability of the model to complex conditions. The "Different Distances" scenario also showed a satisfactory result with an accuracy of 87%. These results confirm that the system effectively copes with various challenges in real-world operating conditions, but some conditions, such as changes in lighting, may require additional tuning.

Conclusion

The obtained test results confirm that the implementation of the MobileNetV2 neural network model for human recognition and identification in the working area of the collaborative robot is successful and effective. Mathematical description of the model demonstrated its ability to achieve high accuracy with minimal computational cost due to the optimized architecture. The implementation of the model in Python using the PyCharm environment made it possible to effectively implement it in real time, which is confirmed by the test results. The high recognition accuracy and speed of the model indicate its potential for practical use in collaborative work, where accurate and fast identification of a person is required to ensure safety and efficiency of interaction. Despite generally positive results, some scenarios, such as varying lighting, require further improvement to improve accuracy in challenging environments. In general, the developed system meets modern requirements for the integration of real-time recognition in robotics.

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