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RESEARCH ARTICLE

Efficiency of YOLO neural network models applied for object recognition in radar images

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Abstract
Objectives. The paper addresses the problem of applying neural networks for object detection in radar images and their recognition under conditions of limited computational resources. The aim was to investigate the speed and recognition quality of YOLO[1] neural network models in solving object detection and classification tasks in radar images in order to evaluate the feasibility of their practical implementation on a microcomputer with a neural processor.
Methods. Machine learning, object detection, and classification techniques were used to detect and classify objects in a radar image.
Results. The study compared the speed and recognition quality of the 5th, 8th, and 11th generation YOLO neural network models with varying numbers of trainable parameters (nano-, small-, medium-, large-, and extra-large-sized) to assess their potential use on a microcomputer with a neural processor. As a result of comparing various YOLO models using evaluation metrics, YOLOv11n (0.925), YOLOv5l (0.889), and YOLOv11s (0.883) showed the highest precision metric; YOLOv5n (0.932), YOLOv11n (0.928), and YOLOv11s (0.914) showed the highest recall metric; YOLOv11s (0.961), YOLOv5n (0.954), and YOLOv11n (0.953) showed the highest mAP50 metric; and YOLOv5n (0.756), YOLOv11s (0.74), and YOLOv5l (0.727) showed the highest mAP50-95 metric.
Conclusions. The conducted research confirmed the feasibility of running YOLO neural network models on a microcomputer with a neural processor, provided that the computational resources of the microcomputer match the computational requirements of the neural networks. The ROC-RK3588S-PC microcomputer (Firefly Technology Co., China) provides up to 6 TOPS of performance, allowing the use of YOLOv5n (7.1 GFLOPs), YOLOv11n (6.3 GFLOPs), and YOLOv11s (21.3 GFLOPs) models.

Keywords: pattern recognition systems, neural networks, radar images, machine learning algorithms

[1] You Only Look Once is a series of neural network models for the real-time object detection.

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НАУЧНАЯ СТАТЬЯ

Исследование эффективности применения моделей нейронных сетей YOLO для распознавания объектов на радиолокационных изображениях

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Резюме
Цели. В статье рассматривается проблема применения нейронных сетей для обнаружения и классификации объектов на радиолокационных изображениях в условиях ограниченных вычислительных ресурсов. Целью работы является исследование быстродействия и точности моделей нейронных сетей YOLO[2] при решении задач обнаружения и классификации объектов на радиолокационных изображениях для оценки возможностей практической реализации на микрокомпьютере с нейронным процессором.
Методы. В работе использовались методы машинного обучения, обнаружения и классификации объектов на изображении.
Результаты. Результатом работы является оценка и сравнение быстродействия и точности моделей нейронных сетей YOLO 5-го, 8-го и 11-го поколений с разным количеством обучаемых параметров (модели nano, small, medium, large, extra large) для исследования возможности их использования на микрокомпьютере с нейронным процессором. При сравнении различных моделей YOLO по метрике оценки точности лучшие результаты показали модели YOLOv11n (0.925), YOLOv5l (0.889), YOLOv11s (0.883); по метрике полноты – YOLOv5n (0.932), YOLOv11n (0.928), YOLOv11s (0.914); по метрике mAP50 – YOLOv11s (0.961), YOLOv5n (0.954), YOLOv11n (0.953); по метрике mAP50-95 – YOLOv5n (0.756), YOLOv11s (0.74), YOLOv5l (0.727).
Выводы. Проведенные исследования показывают возможность применения моделей нейронных сетей YOLO на микрокомпьютере с нейронным процессором при соответствии вычислительных ресурсов микрокомпьютера и вычислительных требований нейронных сетей. Микрокомпьютер ROC-RK3588S-PC (Firefly Technology Co., Китай) обеспечивает быстродействие до 6 TOPS (Тера-операций в секунду), что позволяет применять модели YOLOv5n (7.1 GFLOPs), YOLOv11n (6.3 GFLOPs), YOLOv11s (21.3 GFLOPs).

[2] You only look once (YOLO) – серия нейросетевых моделей для задачи детекции объектов. [You Only Look Once is a series of neural network models for the real-time object detection.]

Ключевые слова: системы распознавания образов, нейронные сети, радиолокационное изображение, алгоритмы машинного обучения

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INTRODUCTION

At present, airborne synthetic aperture radar (SAR) systems are widely used to obtain radar images of terrain [1, 2]. The examples of practical applications of radar imagery produced by SAR airborne radar systems installed on unmanned aerial vehicles (UAVs) include the following:

- vehicle location during search and rescue operations, movement control and security of production plants, storage terminals, fields, ports, and urban areas (parks, water conservation areas), as well as flood detection;
- remote monitoring of extended infrastructure, particularly in remote areas, including oil and gas pipelines, power lines, and railway infrastructure;
- automated creation of digital elevation maps (3D models) of the Earth's surface and classification of the Earth's cover, such as farmland, town, village, water, forest, and road objects.

As a rule, data processing and formation of radar images is performed in stationary conditions using high performance computers. However, in cases where a higher efficiency is required, radar image processing can be carried out on board the UAV. For example, the efficiency of search and rescue operations can be improved by onboard radar image processing and formation by significantly reducing the duration of vehicle search and increasing the efficiency of assistance. This operation can be implemented using neural networks installed on the microcomputers (MC) of the onboard equipment.

The efficiency of ground object detection can be enhanced using various-purpose sensors on the UAV. A new approach to the creation of a multifunctional airborne radioelectronic complex includes the use of various radar modes, the integration of the locator with optoelectronic means, including infrared, as well as the use of airborne radar stations based on synthetic aperture. Modern radar stations ensure high resolution and are capable of performing the tasks of detection and recognition of hidden objects, thus supplementing optical and infrared systems [3].

Radar surveillance using SAR technology is currently considered to be an effective method of remote monitoring of objects of interest, resulting in highly informative 2D radar images. The possibility of obtaining these images is not limited by time of day or meteorological conditions [4, 5].

The basic principles of radar image formation are well known and have been thoroughly discussed previously[3] [6, 7]. When processing SAR data, account should be taken of the specifics of radar imaging, such as:

- geometric and radiometric distortions on the formed radar images;
- the presence of radar shadows;
- speckle noise formed as a result of coherent summation of reflected electromagnetic waves from spatially random scattering sources falling within the SAR resolution element;
- the difference in reflective properties of objects in different frequency ranges;
- radar imaging mode;
- operating frequency range and signal polarization.

At the same time, the basic principles and characteristics of radar image formation are important for the creation of image databases to be further used for training, validation, and testing of neural network models.

The relevance of the research presented in our paper is confirmed by a number of publications. The effectiveness of neural networks for maritime object detection and recognition was investigated in [8–10]. Thus, the work [8] provided accuracy estimates of the YOLOv5x neural network[4] based on the SAR Ship Dataset database [11] using appropriate metrics to evaluate the accuracy of its performance, while [9] investigated neural networks for ship detection and recognition. The results of different neural network

[3] Fundamentals of processing radar data from Earth remote sensing. https://habr.com/ru/articles/787074 (in Russ.). Accessed December 02, 2024.

[4] You Only Look Once is a series of neural network models for the real-time object detection.

models, such as YOLOv4, YOLOv7, YOLOv7-tiny, RetinaNet, Cascade R-CNN, SSD, and OE-YOLO, were described in quantitative terms. In [10], neural networks for object detection and recognition from moving and stationary target acquisition and recognition (MSTAR)[5] databases were analyzed. Different neural network models and their performance characteristics were evaluated using the following metrics: Recall, Precision, mAP50, and mAP50-95.

In this paper, we compare the speed and recognition quality of YOLO neural network models of the 5th, 8th, and 11th generation with different numbers of trained parameters and evaluate the feasibility of their application in an MC with a neural processor.

CREATING A RADAR IMAGE DATABASE

Radar image databases are conventionally created using three main approaches, including:

- experimental imaging of objects of interest on the Earth's surface by means of onboard SAR, taking into account various factors affecting the formation of radar images;
- simulation of the propagation processes of radio waves reflected from the Earth's surface and further processing of the received signals in accordance with the algorithms of SAR operation;
- search of SAR-obtained radar images in open sources.

The former approach provides the most accurate radar image database, although requiring extensive computational and time budgets. Radar image simulation is a complex process whose efficiency depends on numerous factors, such as the complexity of simulating reflections from terrain and extended objects, as well as the formation of a large flow of radar information from SAR receivers, etc. [12, 13].

In this research, we apply the latter approach, which relies on open-source radar image databases to solve the problem. To that end, the open part of the MSTAR database was used. The radar images in this database are formed according to the characteristics of a radar system and the conditions of image formation (see Table 1).

The MSTAR database comprises two datasets, namely:

- MSTAR target, where each image has a plain background and a vehicle in its middle; radar images are taken from different angles of a scene;
- MSTAR clutter, where radar images of rural areas with roads and forests are taken without vehicle images.

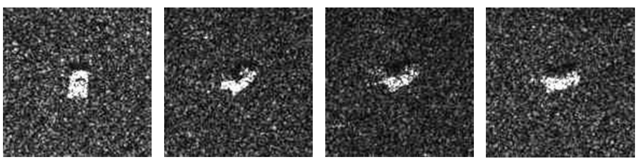
[5] https://www.mathworks.com/help/radar/ug/sar-target-classification-using-deep-learning.html. Accessed December 02, 2024.

Table 1. Radar system characteristics and imaging conditions

Characteristics	Value
Frequency range	X band
Center frequency of the sounding signal	9.6 GHz
Bandwidth of the sounding signal	591 MHz
Radiation and reception polarization	Horizontal
Angle and azimuth resolution	1 foot (~30.5 cm)
Shooting mode	Spotlight
Carrier	Aircraft (Twin Otter)
Carrier speed	140–170 km/h
Inclined range	~5 km
Angles of shooting location from ground plane	15°–45°
Shooting angles in azimuth plane	0°–360°
Weather conditions	Clear, dry
Terrain	Plain
Vegetation	Grassy, low
Season	Autumn (September, November)
Shooting location	US Army installation, Redstone Arsenal, Huntsville

The MSTAR database includes 8890 images of vehicles, 2539 images of radar reflectors, and 100 images of rural areas. The complete list of radar images in the database is presented in Table 2.

Examples of radar images from the MSTAR target database are shown in Fig. 1.



Azimuth 4° Azimuth 38° Azimuth 50° Azimuth 70°

Fig. 1. Examples of radar images from the MSTAR target database

Table 2. List of radar images in the MSTAR database

Target	Description	Angles of site, °	Remarks
T-72	T-72 tank	15	3 sets of 195 images 8 sets of 274 images
		17	3 sets of 230 images 8 sets of 248 images
		30	1 set of 288 images 1 set of 133 images
		45	1 set of 303 images 1 set of 120 images
BMP2	BMP 2 is a tracked infantry fighting vehicle	15 17	3 sets of 196 images 3 sets of 235 images
BTR-60	BTR-60 is an armored personnel carrier (APC)	15 17	1 set of 195 images 1 set of 256 images
BTR-70	BTR-70 is APC	15 17	1 set of 196 images 1 set of 233 images
2S1	2S1 Gvozdika (“Carnation”) is a self-propelled howitzer	15 17 30 45	1 set of 274 images 1 set of 299 images 1 set of 288 images 1 set of 303 images
BRDM-2	BRDM-2 (GAZ-41) is an armored reconnaissance scout vehicle	15	1 set of 274 images
		17	1 set of 298 images
		30	1 set of 287 images 1 set of 133 images
		45	1 set of 303 images 1 set of 120 images
T-62	T-62 tank	15 17	1 set of 273 images 1 set of 299 images
ZSU_23_4	ZSU-23-4 “Shilka” is a self-propelled anti-aircraft gun (SPAAG)	15	1 set of 274 images
		17	1 set of 299 images
		30	1 set of 288 images 1 set of 118 images
		45	1 set of 303 images 1 set of 119 images
ZIL131	ZIL-131 is an expanded mobility truck	15 17	1 set of 274 images 1 set of 299 images
D7	D7 is a tractor-mounted dozer	15 17	1 set of 274 images 1 set of 299 images
SLICY	Construction of geometric figures including basic radar reflector shapes such as flat plate, dihedral, trihedral, and cylinder	15 16 17 29 30 31 43 44 45	1 set of 274 images 1 set of 286 images 1 set of 288 images 1 set of 210 images 1 set of 288 images 1 set of 323 images 1 set of 255 images 1 set of 312 images 1 set of 303 images
CLUTTER	Radar images of Huntsville city and surroundings	15	1 set of 100 images

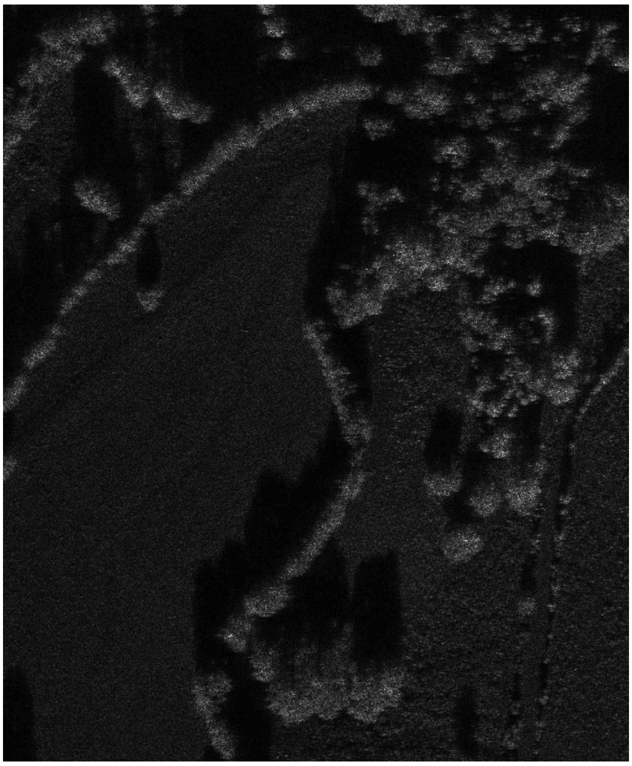


Fig. 2. Rural image from MSTAR cluttered sample

Fig. 3. Example of an image from the created database

A sample image from the MSTAR clutter sample is shown in Fig. 2.

The radar images of the ground surface (MSTAR clutter) and of the vehicles (MSTAR target) are produced under the same conditions. This allows the technique of placing the objects on the background of the rural area to be applied, similar to that reported in [10].

The process of image fusion and generation is performed in three steps [10]:

- selection of the object radar image (MSTAR target) locations on the rural radar image (MSTAR clutter);
- correction of the pixel brightness of the object radar image (MSTAR target) and the selected section of the rural radar image (MSTAR clutter);
- fusion of the object radar image (MSTAR target) and the selected rural radar image (MSTAR clutter).

The MSTAR target angle is equal to the MSTAR clutter angle.

The objects placed in the radar image correspond to the following classes: Class 0 is a radar reflector (SLICY), Class 1 is an armored personnel carrier (APC), Class 2 is an armored reconnaissance scout vehicle, Class 3 is a self-propelled anti-aircraft gun (SPAAG), and Class 4 is a tank. The image from the created database is shown in Fig. 3.

Following the above steps, a database for solving the problem of detecting and recognizing objects on the Earth's surface is created. The sample consists of 350 images with five objects placed on each image. In total, 300 and 50 images are used for training and for validation and testing, respectively. For each image, a text file containing the object coordinates and information about their class is provided.

The speed and recognition quality of the 5th, 8th, and 11th generation YOLO neural network models [14] from the Ultralytics[6] library with different numbers of trained parameters (nano-, small-, medium-, large-, and extra-large-sized models) with the following neural network training parameters were investigated:

- the number of training epochs for all algorithms is 40;
- the optimizer is AdamW with a convergence step of 0.001111, with a momentum equal to 0.9.

TRAINING RESULTS AND PERFORMANCE EVALUATION OF NEURAL NETWORKS

The metrics [9] was used to monitor the training process of the model and to evaluate its performance in the training and validation datasets:

1. Precision is the share of objects that are labelled as positive by the classifier and that are actually positive:

[6] Ultralytics | Revolutionizing the World of Vision AI. https://www.ultralytics.com/. Accessed December 02, 2024.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \tag{1}$$

where TP (True Positive) is the share of correct classifications belonging to a positive class and FP (False Positive) is the share of incorrect classifications belonging to a positive class (type II error, false alarm). This metric evaluates the model for type II errors.

2. Recall is the share of objects of a given class out of all objects of a given class found by the algorithm:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \tag{2}$$

where FN (False Negative) is the share of misclassifications not belonging to a positive class (type I error, target omission). This metric evaluates the model for type I errors.

The precision and recall values are obtained for different model confidence thresholds (confidence levels). These thresholds are set manually and the prediction of the bounding box and the prediction of the model class are estimated simultaneously. At higher thresholds, there are fewer detector responses. However, this will reduce the type II error (FP), thus increasing the accuracy but decreasing the completeness value. It is therefore possible to plot Precision against Recall. The average precision (AP) is the area under the Precision–Recall curve:

$$\text{AP} = \int_0^1 P(R)dR. \tag{3}$$

The mean average precision (mAP) is the area under the Precision–Recall curve weighted across all classes:

$$\text{mAP} = \frac{1}{N}\sum_{i=1}^{N} \text{AP}(i). \tag{4}$$

For example, the mAP50-95 metric is a weighted mean accuracy given the values of IoU $\in$ [0.5; 0.95], where IoU (intersection over union) is a metric of the degree of intersection between the true bounding box and the predicted bounding box. When the predicted bounding box coincides with the true bounding box, IoU = 1.

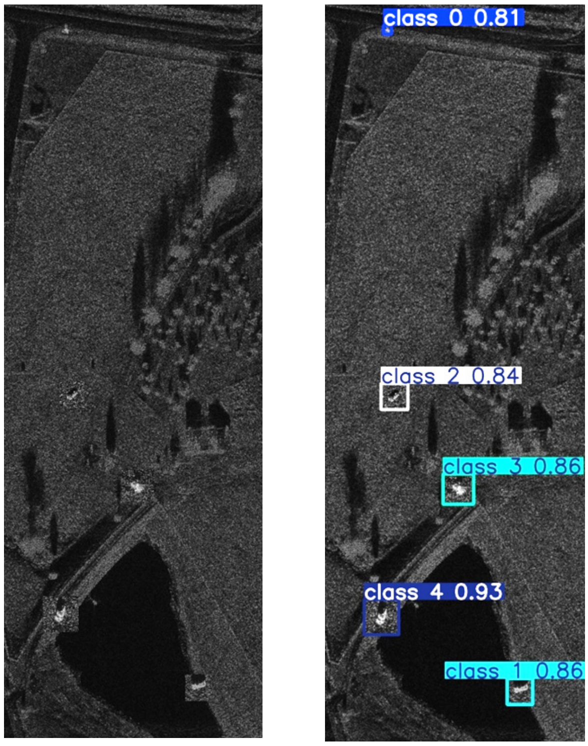
An example of object recognition in the test image is shown in Fig. 4.

At the end of training, the best model is considered to be the one with the highest mAP50-95 metric on the validation data.

The numerical values of the metrics obtained during the training of the neural networks of the YOLO family are given in Table 3.

Comparing different YOLO models showed the following: the top three models by precision are YOLOv11n (0.925), YOLOv5l (0.889), and YOLOv11s (0.883). YOLOv5n (0.932), YOLOv11n (0.928), and YOLOv11s (0.914) show the highest recall metric; YOLOv11s (0.961), YOLOv5n (0.954), and YOLOv11n (0.953) show the highest mAP50 metric; and YOLOv5n (0.756), YOLOv11s (0.74), and YOLOv5l (0.727) show the highest mAP50-95 metric.

The analysis of the number of floating-point operations are represented by a histogram in Fig. 5.



(a) (b)

Fig. 4. Results of object recognition in a radar image using the YOLOv11s model: (a) radar image before recognition; (b) radar image after recognition

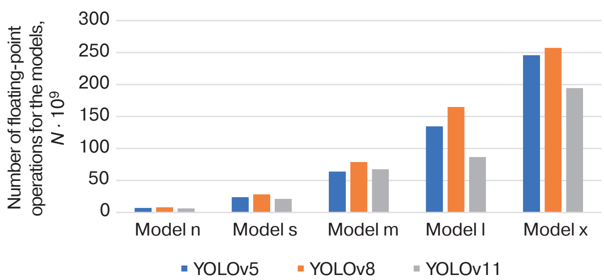


Fig. 5. Comparison of the number of floating-point operations for the models under study

The results obtained allow us to conclude that models l and x with more floating-point operations outperform models n, s, and m in terms of all parameters, largely due to undertraining of models l and x.

Table 3. YOLO neural network model metrics

Neural network model	Precision	Recall	mAP50	mAP50-95	Number of floating-point operations
YOLOv5n	0.844	**0.932**	0.954	**0.756**	7.1e9
YOLOv5s	0.76	0.808	0.871	0.649	23.8e9
YOLOv5m	0.789	0.801	0.889	0.695	64e9
YOLOv5l	0.889	0.881	0.933	0.727	134.7e9
YOLOv5x	0.725	0.802	0.844	0.678	246e9
YOLOv8n	0.748	0.84	0.897	0.65	8.1e9
YOLOv8s	0.643	0.79	0.828	0.617	28.4e9
YOLOv8m	0.739	0.832	0.871	0.678	78.7e9
YOLOv8l	0.694	0.806	0.843	0.648	164.8e9
YOLOv8x	0.772	0.821	0.895	0.697	257.4e9
YOLOv11n	**0.925**	0.928	0.953	0.725	6.3e9
YOLOv11s	0.883	0.914	**0.961**	0.74	21.3e9
YOLOv11m	0.804	0.893	0.91	0.726	67.7e9
YOLOv11l	0.566	0.7	0.761	0.573	86.6e9
YOLOv11x	0.63	0.772	0.82	0.627	194.4e9

For the mAP50 and mAP50-95 metrics, the highest results are achieved using the YOLOv5n, YOLOv11n, and YOLOv11s models. In [10], FasterRCNN (mAP50 = 0.8786), RetinaNet (mAP50 = 0.916), and different modifications of YOLOv5 such as YOLOv5 basic (mAP50 = 0.9169) and YOLOv5 modified (mAP50 = 0.9555) were used to investigate recognition accuracy. For comparison, the YOLO neural network models and the values of the mAP50 metric are shown in Table 4.

Table 4. The mAP50 metric of neural network models

Neural network model	mAP50
YOLOv5n	0.954
YOLOv11n	0.953
YOLOv11s	**0.961**

The data presented in Table 4 indicate that the 11th generation YOLO models perform sufficiently well in solving the problem of ground object detection and recognition in radar images.

The error matrix for the YOLO neural network is shown in Fig. 6, which indicates the number of misclassifications made by the model. The classes as predicted by the model are labelled on the left, and the true classes are labelled at the bottom. In addition to the five classes of recognized objects, there is also a background class representing the background classification errors.

It can be assumed that images of radar reflectors were classified as background more often than others, due to their small effective scattering area compared to the other classes.

When predicting Class 1, the YOLOv11s model has the maximum type I error with 5 out of 50 classified as Class 2 and 6 out of 50 classified as Class 4. Class 4 has the maximum type II error with 6 objects of Class 1, 3 objects of Class 3, and 3 snippets with background classified as Class 4.

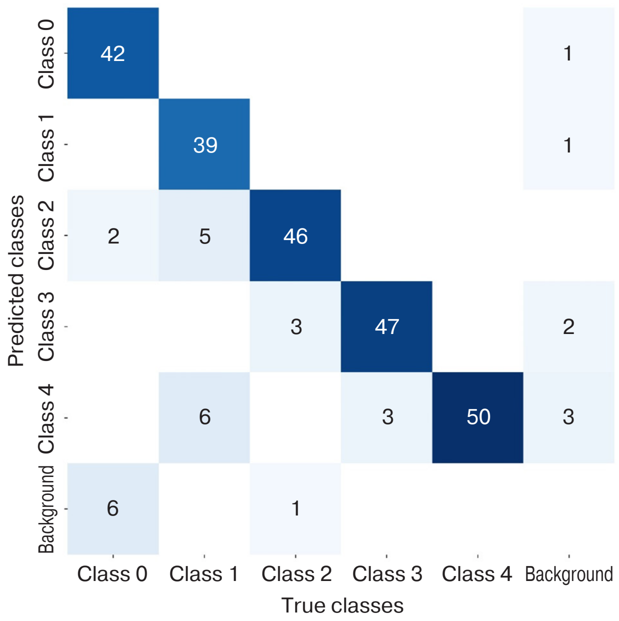


Fig. 6. Error matrix for the YOLOv11s neural network

In [15], in order to evaluate the feasibility of using neural networks on MCs, the number of operations required by the YOLO model was compared to the number of operations per second that can be provided by the MC. The Firefly ROC-RK3588S-PC (Firefly Technology Co., China) was used as a basis, equipped with an onboard RK3588 neural processor capable of up to 6 Tera operations per second (TOPS)[7].

The computational resources consumed by a neural network model on a single input image can be expressed in terms of Giga float operations (GFLOPs). For a relevant evaluation, it is necessary to convert TOPS into a floating-point format, since TOPS defines the number of operations per second[8] and GFLOPs defines the number of floating-point operations with the input image. The performance of 4 TOPS is approximately equal to the performance of 1 TFLOPS[9]; hence, converting 6 TOPS results in 1.5 TFLOPS. Therefore, the performance of the ROC-RK3588S-PC MC allows the installation of YOLOv5n (7.1 GFLOPs), YOLOv11n (6.3 GFLOPs), and YOLOv11s (21.3 GFLOPs), providing a performance of more than 10 frames per second, which is a positive result.

CONCLUSIONS

Our research demonstrates that, out of the neural network models considered, the YOLOv5n, YOLOv5l, YOLOv11n, and YOLOv11s models produce the highest results in terms of the following metrics. The difference in the mAP50-95 metrics between the YOLOv5l and YOLOv11n models is ~0.003. The difference in the Precision metric values between YOLOv5l and YOLOv11s models is ~0.006. The difference in the computational cost is ~102 floating point operations, which has a significant impact on performance. The selected models are therefore YOLOv5n, YOLOv11n, and YOLOv11s. According to their computational costs and the performance of the ROC-RK3588S-PC MC, the selected models can be recommended for installation on the MC for real-time operation.

Authors' contributions

A.S. Krasnoperova—conducting research, interpreting and summarizing results, writing the text of the article.

A.S. Tverdokhlebov—interpreting research results, preparing conclusions.

A.A. Kartashov—defining the research topic and discussing the final text of the article.

V.I. Weber—planning the research, interpreting results, scientific editing of the article.

V.Y. Kuprits—setting the aims and objectives of the research, methods of machine learning.

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