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Analysis of Hardware-Computing Modules and Neural Networks for Aviation Surveillance Systems with Computer Vision

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***Abstract* — The paper proposes a hardware and software system for the tasks of recognizing physical ground objects in the flow of radar frames on the basis of a single-board computing module located on a small aircraft. Hardware computing modules with neural network processing blocks are analyzed. Small-size neural network models for their deployment on the hardware-computing module are analyzed and selected. The hardware-software system of airborne basing with realization of recognition of physical ground objects in the stream of radar frames is described.**

Keywords — recognition; physical ground objects; radar images; computer vision; hardware computing modules; compact neural networks; aviation surveillance.

I. Introduction

In recent years, compact Synthetic Aperture Radar (SAR) systems have found widespread applications. This trend is driven by global progress in science and technology, its integration with small aerial vehicles (SAVs). Modern SAVs with takeoff mass of several kilograms (from 5 kg) possess sufficient payload capacity to carry compact radar systems equipped with hardware computing modules [1].

Compact SAR systems mounted on SAVs can generate high-resolution radar image streams [2]. This imaging method remains unaffected by various disruptive factors, including temporal and seasonal visibility conditions such as fog, smoke, smog, snowfall, or cloud cover. Therefore, the resulting radar image provides reliable information about physical ground objects (PGOs). This capability enables continuous monitoring of man-made and natural emergency situations (ES), across challenging Earth surface observation conditions.

Due to the specific nature of radar image generation, specialized approaches capable of automatic PGO recognition are required. To enable such continuous monitoring of both man-made and natural emergency situations, SAV-based systems require neural network models that can automatically detect PGOs in generated radar images [3].

II. Problem Statement

Conventional neural network-based approaches often prove unsuitable for real-time operation aboard SAVs due to high computational demands for radar image processing. This necessitates an analysis to establish technical recommendations for implementing an hardware computing system capable of real-time operation and automated aerial monitoring of ES zones.

The solution to this problem may involve using compact neural network architectures [4], implemented on portable and small-sized hardware computing modules (HCMs). The HCM foundation is proposed to be based on single-board computers using specialized processors designed for high-speed neural network execution. This combination of HCMs with specifically tailored neural network architectures will enable SAVs to achieve the required speed of neural network data processing (NNP) that meets soft real-time requirements and high accuracy of correctly recognized PGOs in autonomous ES zones monitoring mode.

Thus, to solve the stated problem, the following steps must be performed:

- Conduct an analysis of small-sized hardware HCMs and select the most suitable for aviation monitoring purposes;
- Perform an analysis of compact neural network models for PGOs recognition in radar image streams and make

a selection considering processing speed and recognition accuracy requirements;

- Based on the conducted analyses of HCM and neural network model selection, formulate recommendations for implementing an aviation monitoring system capable of recognizing PGOs in radar image streams while meeting all the aforementioned requirements.

III. HARDWARE COMPUTING MODULES ANALYSIS AND SELECTION

To address the task of recognition in radar image streams, it is necessary to evaluate small-sized HCMs. The key parameters for analysis include the specifications of the following HCM components: Central Processing Unit (CPU), Graphics Processing Unit (GPU), Neural Processing Unit (NPU), Random Access Memory (RAM) capacity and Physical dimensions (PD) of HCM.

For NPUs, their computational performance is measured in trillions of operations per second (TOPS).

Table I presents the most popular HCMs [5-8], especially:

- Raspberry Pi 5 Model B;
- Orange Pi 5 Plus;
- NVIDIA Jetson Nano B;
- Salute-EL24PM;
- 'NanoS'/PicoS with digital signal processors (DSPs);
- 'NanoR'.

TABLE I. HARDWARE COMPUTING MODULES ANALYSIS

HCM	**HCM performance parameters**				
	CPU	**GPU**	**NPU, TOPS**	**RAM, GB**	**PD, mm**
Raspberry Pi 5 Model B	4-core Cortex-A76 (2.4 GHz)	Broadcom VideoCore VII (OpenGL ES 3.1).	–	Up to 8 GB LPDDR4	85 x 56
Orange Pi 5 Plus	8-core (4×A76 + 4×A55, up to 2.4 GHz)	Mali-G610 MP4 (OpenGL ES 3.2, Vulkan 1.2)	6	Up to 32 GB LPDDR4/5	100x 75
NVIDIA Jetson Nano B	4-core ARM Cortex-A57 (64-bit) 1.43 GHz.	NVIDIA Maxwell (128 CUDA-cores)	–	4 GB LPDDR4 (25.6 GB/s)	69.6 x 45
Salute-EL4PM	2-core CPU Cortex-A9, up to 816MHz; 2-core DSP «ELcore-30M», up to 672MHz;	Mali-300	2 GB LPDDR3		60x60
NanoS	1892VA018 SKIF, 4-core ARM Cortex-A53 up to 2 GHz additional DSP Elcore-50	–	1.2	8 GB LPDDR4	120×120
PicoS	1892VA018 SKIF, 4-core ARM Cortex-A53 up to 2 GHz additional DSP Elcore-50	–	1.2	8 GB LPDDR4	100x70
NanoR	RK3588 8-core ARM Cortex-A76	Mali-g610	6	8 GB LPDDR4	120x120

As can be seen from Table 1, for neural network frame processing tasks, the following four HCMs stand out: Jetson Nano (with support for the parallel computing hardware-software architecture 'Nvidia CUDA') [9] and Orange Pi 5 Plus with built-in neural processing blocks. At the same time, there is an analogue to the well-known Rockchip processor, which is installed on the HCM "NanoS/PicoS" under the name «SKIF» [10].

1. The 'NVIDIA Jetson Nano' HCM is optimal for neural network models due to its 128-core CUDA GPU and TensorRT support, enabling real-time frame processing at 15-20 Hz through YOLO-family model implementations. This module's key distinction is its seamless integration with AI ecosystems, especially with the 'PyTorch', 'TensorFlow', and 'OpenCV' libraries, along with CUDA-core optimization capability for radar image processing. However, its weak 4-core CPU (Cortex-A57) may bottleneck high-resolution image processing, and its 5W power consumption requires active cooling for sustained operation.

2. The 'Orange Pi 5 Plus' HCM (featuring RK3588 CPU and Mali-G610 GPU) stands out with its 8-core CPU (4-core Cortex-A76 and 4-core Cortex-A55) and integrated NPU delivering up to 6 TOPS. This configuration enables 40 FPS processing for optimized neural networks like YOLOv8n. However, NPU adaptation via the RKNN-Toolkit library [11] requires time, and available documentation poorly addresses non-standard input data formats. For stable peak-load operation, the module requires up to 20W power draw and active cooling for the HCM processor.

3. The "NanoS" HCM ("Cortex-A53" CPU and "Elcore-50" DSP) - stands out due to its "Elcore-50" DSP, designed for processing image streams in object recognition tasks through its ability to perform highly efficient mathematical operations in real time.

4. The "PicoS" HCM is based on a quad-core ARM Cortex-A53 processor (up to 2 GHz) with an Elcore-50 optimized for processing neural network algorithms and mathematical operations in real time. The module supports Linux operating systems (AltLinux, Red hat, Buildroot) and is equipped with MIPI-CSI-2 interfaces.

5. The "NanoR" HCM (RK3588 CPU and Mali-G610 GPU) demonstrates similar specifications to the Orange Pi 5 Plus. The Mali-G610 provides basic graphics processing, and the 8-core CPU can handle data preprocessing. However, the

lack of specialized AI accelerators (NPU/GPU) limits the frames per second for neural networks, and the ecosystem depends on manufacturer support.

Based on the analysis, we can conclude that among competing solutions, the Rockchip OrangePi 5 Plus-based HCM stands out for its fast neural data processing accelerated by a dedicated NPU.

At the same time, HCM based on NVIDIA Jetson Nano achieves comparable performance by utilizing CUDA cores for parallel computing.

And among the non-Rockchip-based counterparts, the “PicoS” HCM is the optimal solution for recognizing PGOs in radar images. Its key advantages include its compact size and DSP support that minimizes processing latency and meets the requirements of soft real-time operation.

IV. ANALYSIS AND SELECTION OF NEURAL NETWORKS FOR PHYSICAL GROUND OBJECT RECOGNITION IN RADAR IMAGE STREAMS ON HARDWARE COMPUTING MODULES

For implementing PGO recognition in radar image streams [12] onboard SAVs through HCM deployment, the following compact neural network architectures should be considered (Fig. 1):

- MobileNet-SSDLite models of various versions [13];
- YOLO-Tiny family models [14];
- YOLOv nano version [15, 16].

These neural network models are suitable for operation under limited computational resources, meaning they can be implemented onboard SAVs with 1-2 GB of RAM and low processing power while maintaining sufficient recognition accuracy of PGOs. The architectures of compact neural network models (Fig. 1) with simplified structure (fewer layers) are applicable for neural network processing of radar images. They are perfectly suited for implementation onboard SAVs for the purpose of automatic aviation monitoring of ES zones.

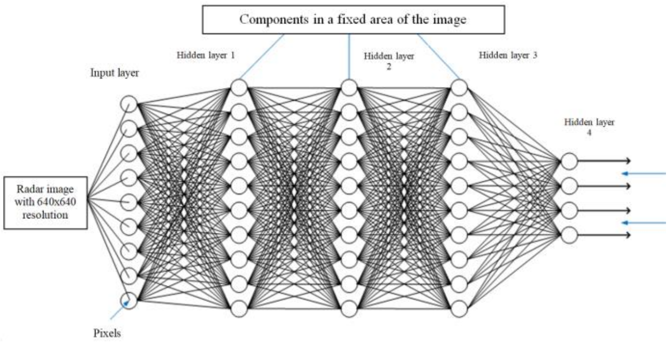

Fig.1. Neural Network Architecture

Table II presents the comparative analysis of neural networks (NNs) based on the following key parameters: model size (in megabytes, MB), mean accuracy prediction (mAP), number of trainable parameters (in millions), floating-point operations per second (FLOPS).

TABLE II. ANALYSIS OF NEURAL NETWORKS FOR PGO RECOGNITION IN RADAR IMAGE STREAMS

Neural Network	**NN performance parameters**				
	№	**Model Size, MB**	**Number of Trainable Parameters, mln**	**FLOPs**	**mAP**
MobileNet SSDLite	v1	7	4.2	1.0	0.5
	v2	17	10	1.5	0.7
	v3	19	5.4	1,2	0.71
YOLO-Tiny	v5	13.7	5.1	5.8	0.65
	v7	11	6	6.1	0.72
YOLO nano version	v5n	3.9	1.9	4.5	0.75
	v8n	8	3.2	8.7	0.86

As can be seen from Table 2, the neural network YOLOv8n stands out for the given task due to its processing speed and mean prediction accuracy of PGOs in radar images on HCMs [17-19].

Training such neural network models requires specialized datasets of radar images, as real data is often unavailable. The open datasets of radar images for training neural network models include: Moving and Stationary Target Acquisition and Recognition (MSTAR) [20], Mini SAR [21], Spotlight SAR [22], FARAD X BAND [23], FARAD KU BAND [24], SARDet-100k, OGSOD, SAR-Aircraft, SSDD.

Therefore, for a PGO recognition system in ES zones, it is necessary to prepare a dataset of radar images, annotate them, modify the neural network model architecture, and conduct experiments to demonstrate the results [25, 26].

V. HARDWARE-SOFTWARE SYSTEM FOR PHYSICAL GROUND OBJECT RECOGNITION IN RADAR IMAGE STREAMS

Thus, for implementing the aviation monitoring system, it is recommended to use the PicoS HCM with a NPU of up to 6 TOPS. To ensure continuous operation, power is provided through a multi-level DC/DC converter that stabilizes component voltage [27-29]. For autonomous operation of the hardware system, a lithium-polymer battery with a charge controller is used, which requires an active cooling system.

The software part is implemented on the Linux RT operating system for processing radar image streams with support for Rockchip RKNN and TF-Lite libraries [30, 31].

Thus, use of a compact neural network model based on an HCM with a built-in NPU block implements an autonomous PGO recognition system through the use of the compact YOLOv8n neural network, which provides minimal processing result display latency, corresponding to soft real-time mode. At the same time, the power consumption of the HCM is in the range of 5-10 W, which is also feasible onboard SAVs.

VI. Conclusion

Thus, in this work, compact HCMs were analyzed. For the stated task, the 'Orange Pi 5 Plus' HCM with 'RK3588' processor was selected, where the built-in NPU block increases neural network processing speed up to 6 TOPS, which is essential for processing streaming data in real-time mode.

An analysis of compact neural network models for PGO recognition in radar frame streams was conducted, and for the selected HCM the YOLOv8n model network was proposed, whose advantage over other models is its processing speed of streaming images and high proportion of correctly recognized PGOs.

Based on the conducted analyses of hardware computing module and neural network model selection, recommendations were formulated for implementing an aviation control system performing PGO recognition in radar images streams.

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