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ИНТЕЛИГЕНТЕН СЕНЗОР ЗА ОТКРИВАНЕ НА ПОЖАР С ДЪЛБОКИ НЕВРОННИ МРЕЖИ

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INTELLIGENT SENSOR FOR FIRE DETECTION WITH DEEP NEURAL NETWORKS

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***Abstract*— The current paper presents a sensor using artificial intelligence for fire detection. The sensor uses a new platform for artificial intelligence – AI HAT based on Kendryte K210 processor. The low cost of the platform makes it suitable for implementation in various sensors. One application of the fire detection sensors with AI is for detection of flames in places where other types of fire detection sensors have drawbacks. Such places can be rooms or production facilities where the environment temperature is high, where is a presence of smoke and also presence of hot objects.**

Keywords— Deep Neural Networks, CNN, object detection, fire detection, sensor

I. Introduction

The fire detection systems with high accuracy and reliability are essential for the safety conditions of life in smart cities. Since the traditional fire detection systems can make false alarms, they occasionally push the system operators to take risky actions such as turning off these low-precision fire detection systems [1]. Improving fire detection systems could prevent many accidents due to fires. During 2009–2012, excluding malicious calls 48% of all fire alarms were false alarms [2]. Of all 6,684,500 fire accidents in United States, 4,879,685 cases occurred where fire detection systems were installed [3]. Unfortunately, 20% of the fire detection systems do not correctly work [1]. Commercial fire detection systems generally have a simple sensor with low accuracy and are sensitive to sensor failure and malfunction which makes it hard to detect fires [4]. In addition, even if the sensor is operating normally, faults may occur in the system because of the limitations of the detection capability of the sensor. A smoke sensor may send false alarms because of the incorrect recognition of present dust as smoke [5]. To overwhelm these disadvantages of fire detection systems it can be used the modern technologies for artificial intelligence (AI) and image recognition [6].

II. Overview

The systems for fire detection with high accuracy are very important for facilities where fire can occur. Since the traditional approaches for fire detection – using smoke detectors, heat detectors and ionization smoke detectors have some drawbacks based on their principle of operation in the current paper is presented a fire detection system using camera and implementing artificial intelligence (AI). The proposed system is based on a specialized chip for accelerating the DNN processing. It makes possible the improvement of accuracy when machine vision fire detection system is built

III. Hardware of the system

The system hardware based on AI HAT edge computing kit which is built with the processor Kendryte K210 [6]. This is a powerful low-cost board for artificial intelligence that can work as a standalone board or to be connected to other boards such as Arduino for developing various applications. The board has a 16-bit neural network processor and dual core 64-bit CPU. In addition to that the board has multiple peripherals such as PWM / SPI / I2C GPIO and interfaces for LCD display and camera. Fig. 1 presents the

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development board based on mentioned processor, which is used for designing of fire detection system.

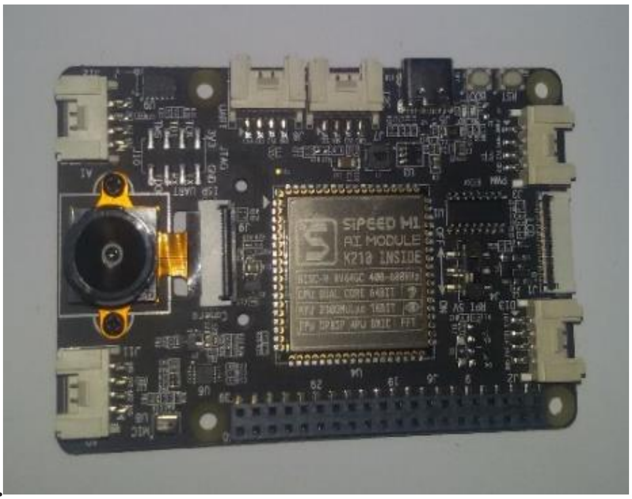

Fig. 1. AI HAT for edge computing

For detection of fire is used camera, which is connected to the board by the DVP interface. The images acquired by the camera are recognized by DNN implemented in the processor module.

IV. Algorithm of operation

The algorithm of system operation includes the following steps:

1. Initialization of system – after power-on, the system is initialized and the periphery of AI HAT module is prepared for data exchange.

2. Reading image from camera – the camera is used for continuous acquiring of images which are resized and feed to the DNN inputs.

3. Applying Deep Neural Network for detection of fire. The resized image from the camera is classified by the DNN.

4. If the neural network locates a fire in the image, an alarm is issued. The sensor module activates one of its outputs in response of this alarm.

V. Yolo DNN Architecture

YOLO stands for ("you look only once") and it is used for detection and classification. It brings a trained neural network which predicts bounding boxes and class probabilities. It finds the location of the image where specific object is present. Other neural networks such as R-CNN use a pipeline for performing tasks in multiple steps which is very hard to optimize. An image from the camera or some other external source is being passed to the neural network and a vector of bounding boxes and a classifier is being returned.

Figure 2 represents the structure of YOLO and the layers in it.

Name	Filters	Output Dimension
Conv 1	7 x 7 x 64, stride=2	224 x 224 x 64
Max Pool 1	2 x 2, stride=2	112 x 112 x 64
Conv 2	3 x 3 x 192	112 x 112 x 192
Max Pool 2	2 x 2, stride=2	56 x 56 x 192
Conv 3	1 x 1 x 128	56 x 56 x 128
Conv 4	3 x 3 x 256	56 x 56 x 256
Conv 5	1 x 1 x 256	56 x 56 x 256
Conv 6	1 x 1 x 512	56 x 56 x 512
Max Pool 3	2 x 2, stride=2	28 x 28 x 512
Conv 7	1 x 1 x 256	28 x 28 x 256
Conv 8	3 x 3 x 512	28 x 28 x 512
Conv 9	1 x 1 x 256	28 x 28 x 256
Conv 10	3 x 3 x 512	28 x 28 x 512
Conv 11	1 x 1 x 256	28 x 28 x 256
Conv 12	3 x 3 x 512	28 x 28 x 512
Conv 13	1 x 1 x 256	28 x 28 x 256
Conv 14	3 x 3 x 512	28 x 28 x 512
Conv 15	1 x 1 x 512	28 x 28 x 512
Conv 16	3 x 3 x 1024	28 x 28 x 1024
Max Pool 4	2 x 2, stride=2	14 x 14 x 1024
Conv 17	1 x 1 x 512	14 x 14 x 512
Conv 18	3 x 3 x 1024	14 x 14 x 1024
Conv 19	1 x 1 x 512	14 x 14 x 512
Conv 20	3 x 3 x 1024	14 x 14 x 1024
Conv 21	3 x 3 x 1024	14 x 14 x 1024
Conv 22	3 x 3 x 1024, stride=2	7 x 7 x 1024
Conv 23	3 x 3 x 1024	7 x 7 x 1024
Conv 24	3 x 3 x 1024	7 x 7 x 1024
FC 1	-	4096
FC 2	-	7 x 7 x 30 (1470)

Fig. 2. Structure of YOLO

Yolo's last layer is using a linear activation and all other layers use a leaky RELU transfer function.

VI. Training the neural network

A neural network has been trained with YOLO architecture which has high speed and accuracy for detecting various objects [7]. The training requires a preliminary database of photos (some of them shown on Fig. 3) from which it is necessary to extract the characteristics of the objects which have to be found after that. The neural network is trained using the library for machine learning TensorFlow-GPU. The neural network is able to recognize multiple objects and by doing software filtering it determines which object is fire and which is not in the image.

Fig. 3. Some of the photos for training the neural network

For training of the neural network for finding fire more than 500 images were used. The images are additionally processed with Python script and new batch of 2000 images with shifted positions of fires are generated. Extracting their characteristics and pixel annotations, the training process of the neural network with YOLO architecture was done for 150 000 cycles until reaching the desired accuracy.

The trained neural network can be implemented in various processing devices such as CPU, GPU and VPU.

In this case the neural network is implemented in the flash memory of GROVE AI HAT. It classifies the objects that are in the image data.

VII. Software used for implementation of algorithm

The main software tool used for current implementation is Tensor Flow Lite. TensorFlow Lite is a set of tools to help developers run TensorFlow models on mobile, embedded, and IoT devices. The TensorFlow Lite converter, which converts TensorFlow models into an efficient form for use by the interpreter, and can introduce optimizations to improve binary size and performance.

All scripts for training and scripts for image processing are written in Python language.

VIII. Experimental results

After training, the YOLO network is downloaded in AI HAT kit. The trained network can detect fire under different conditions of the background. The neural network was tested with the test images which were not included in training process. Fig. 4 presents some of the test images in the way as the AI HAT kit detects the fire and shows its position on the accompanying LCD screen.

Fig. 4. Detecting fire in test images

The network processes the raw signal, coming from the camera. The acquired video frame is being resized with resolution 224x224 and scanned by the trained YOLO neural network. When a flame is detected with high percentage of truth in the video frame, its pixels coordinates are returned by the neural network. The application program draws a rectangular frame around the detected fire mapping all fiery pixels inside it and activate an alarm which can control external fire extinguisher. The system has a high processing speed of the neural network, which is measured to be about 15 ms.

IX. Future work

The neural network of the AI sensor can be further improved to detect more than just fire, for example it can be trained in the future to detects smoke or electric sparks caused by short circuits.

X. Conclusions

The proposed AI sensor can replace multiple sensors at once, it has high accuracy and relatively low cost. The artificial intelligence brings a great improvement in data interpretation from low-cost cameras and can be implemented in new products which complement the already well-known solutions.

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