APPLICATION OF MACHINE LEARNING FOR QUALITY CONTROL IN MANUFACTURING WITH MOBILENETS MODELS

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ЗАСТОСУВАННЯ ТЕХНОЛОГІЙ МАШИННОГО НАВЧАННЯ ДЛЯ КОНТРОЛЮ ЯКОСТІ НА ВИРОБНИЦТВІ ЗА ДОПОМОГОЮ МОДЕЛЕЙ MOBILENETS

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ПРИМЕНЕНИЕ ТЕХНОЛОГИЙ МАШИННОГО ОБУЧЕНИЯ ДЛЯ КОНТРОЛЯ КАЧЕСТВА НА ПРОИЗВОДСТВЕ ПРИ ПОМОЩИ МОДЕЛЕЙ MOBILENETS

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The practicability of using machine learning in manufacturing to control product quality is analyzed in this paper. A family of models for image classification called MobileNets was considered. The optimal values of the model parameters were found.

Keywords: *quality control, machine learning, neural networks, TensorFlow, MobileNet*

У статті проведено аналіз доцільності застосування технологій машинного навчання на виробництвах для контролю якості продукції. Було розглянуто сімейство моделей для класифікації зображень MobileNets. Знайдено оптимальні значення параметрів моделі.

Ключові слова: *контроль якості, машинне навчання, нейронні мережі, TensorFlow, MobileNet*

В статье проведен анализ целесообразности применения технологий машинного обучения на производствах для контроля качества продукции. Было рассмотрено семейство моделей для классификации изображений MobileNets. Найдены оптимальные значения параметров модели.

Ключевые слова: *контроль качества, машинное обучение, нейронные сети, TensorFlow, MobileNet*

INTRODUCTION

Just like the first industrial revolution of the second half of the eighteenth century, which made the transition from manual to mechanized production and had a colossal effect on the manufacturing economy and average household incomes, the third industrial revolution, through the use of computers and information technology, led to the transition to automated production. However, even as of 2019, there are still numerous processes in manufacturing that can be automated. One of these processes is a quality control of products carried out according to external criteria.

Since this quality control involves a comprehensive analysis of an object, namely color, proportions, geometric properties, etc., application of machine learning, which is capable of identifying the quality criteria independently, reduces the cost of developing and tweaking the algorithm in case of minor changes in the technological process [1].

The purpose of this work is to analyze the machine learning practicability for the product classification in manufacturing as a mean of quality control.

Of the well-known software libraries for machine learning (such as TensorFlow, Torch, Caffe, etc.), an open source software library TensorFlow was chosen. TensorFlow is the leader among machine learning libraries, it has Google support and is capable of solving numerous tasks, including the classification of images.

A family of models for the computer classification of images named MobileNets was studied. These models are designed primarily for mobile devices, which ensures their simplicity and speed. The use of simple models may prove to be very successful, and possibly be an optimal solution for those Ukrainian enterprises that are not able to spend $1000 per conveyor row on the hardware required to run complex models.

In addition to the base model, the MobileNets family includes modified versions of the base model. These modifications offer simplifications to the base model (hence the performance increase), but in turn provide lower accuracy [2].

The objective of this study was to explore the capabilities of the MobileNets models family, analyze the feasibility of using them to classify products in manufacturing and to find the optimal model parameters for a specific object.

EXPERIMENTS

A standard pavement tile was chosen as an object for this study. The training data for neural network consisted of 45 images with undamaged tiles and 63 images with damaged ones. To measure the accuracy, we used a set of 10 images that were not included in the training data — 5 undamaged and 5 damaged tiles.

The model was run on a PC with an Intel Core i3-4020Y 1.50GHz processor. The choice of a low-end CPU like this one should demonstrate MobileNets' level of speed and tell us whether it is possible to use budget hardware to control product quality. The following set of software was used: Windows 10 operating system (Version10.0.17134 Build 17134), Python 3.7.2, TensorFlow 1.13.0-rc.

The trained base model demonstrated an average accuracy for ten reference images of 97.98% and an average processing time of 2.517 seconds. These results are generally satisfactory and justify the use of machine learning to control product quality in manufacturing.

When simplified versions of model with modified parameters were analyzed, the following two parameters, which can be varied, were considered: width multiplier and resolution multiplier. Their effect on the processing time and the accuracy of the result was studied.

The width multiplier allows the model to be narrower, in a sense that for each of the layers it reduces the number of input and output channels, thereby simplifying the math. By default, this parameter is equal to 1 [2]. We have studied models with width multipliers 0.75, 0.5, 0.25.

The resolution multiplier reduces the input image resolution. This can make it so some small details or elements in the photo may be missed in the process of training or classification. The base input resolution is 224×224 [2]. Models with resolutions 192×192, 160×160, 128×128 were also studied.

The methodology of the experiment is as follows (fig. 1). For each value of the width multiplier a model was run for each of the 10 reference images. The results are shown in table 1.

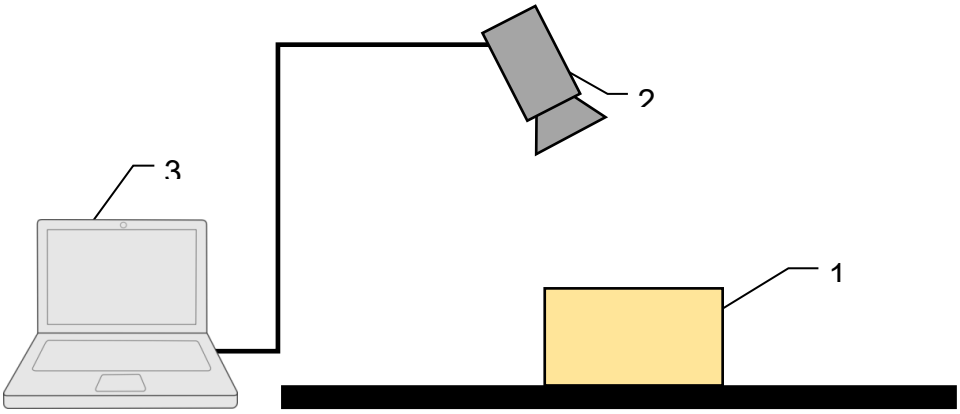

Fig. 1. General scheme of the experimental setup:
1 – Object for classification; 2 – Camera; 3 – PC

Table 1. Dependence of accuracy and processing time on the width multiplier

Image #	Accuracy, %				Processing time, seconds			
	Width multiplier							
	0.25	0.5	0.75	1.0	0.25	0.5	0.75	1.0
1	100	72.22	98.08	92.51	0.359	0.829	1.453	2.484
2	100	56.06	99.29	99.99	0.344	0.812	1.453	2.515
3	100	100	81.90	98.52	0.375	0.812	1.5	2.515
4	100	99.67	99.85	100	0.375	0.797	1.453	2.515
5	100	98.63	25.78	100	0.359	0.812	1.453	2.562
6	100	100	100	100	0.375	0.812	1.453	2.578
7	100	100	100	100	0.359	0.812	1.453	2.5
8	100	100	99.99	88.82	0.359	0.828	1.50	2.5
9	100	100	99.94	100	0.359	0.812	1.453	2.5
10	99.93	100	100	100	0.375	0.812	1.437	2.5
Avg.	**100**	**92.66**	**90.48**	**97.98**	**0.364**	**0.814**	**1.461**	**2.517**

From the results of the first experiment (Table 1), the following conclusions can be made:

- processing time is directly proportional to the width multiplier;
- reducing the width multiplier can not only negatively affect accuracy, but also increase it.

It should be noted that for the instances where accuracy differs significantly from 100% (for example, the accuracy value for the fifth image with width multiplier of 0.75), the models were retrained using the same data. The resulting absolute error was no more than 5%. At the same time, for accuracy values above 95%, the absolute error was no more than 0.1%. Model processing time remained the same.

Table 2 shows the results reflecting the dependence of the resolution multiplier on processing time and accuracy of the solution. From the results of the second experiment (Table 2), the following conclusions can be made:

- processing time becomes slightly lower with resolutions 192×192, 160×160, 128×128, however base resolution processing time is comparable to the one of 160×160;

- a decrease in the input resolution leads to a loss of accuracy, but this dependency is non-linear.

Table 2. Dependence of accuracy and processing time on the input resolution

Image #	Accuracy, %				Processing time, seconds			
	Input resolution							
	128	160	192	224	128	160	192	224
1	97.76	100	98.78	92.51	2.538	2.572	3.013	2.484
2	17.63	100	72.54	99.99	2.503	2.492	2.919	2.515
3	99.99	100	99.99	98.52	2.516	2.54	2.919	2.515
4	100	90.78	99.83	100	2.526	2.496	2.953	2.515
5	100	69.46	100.00	100	2.485	2.479	2.801	2.562
6	100	100	100	100	2.568	2.528	2.866	2.578
7	100	100	99.90	100	2.481	2.524	2.819	2.5
8	100	93.67	88.97	88.82	2.481	2.559	2.72	2.5
9	100	100	11.03	100	2.492	2.503	2.908	2.5
10	99.77	99.55	100	100	2.499	2.562	2.733	2.5
Avg.	**91.52**	**95.35**	**87.10**	**97.98**	**2.509**	**2.526**	**2.865**	**2.517**

SUMMARY

Based on the obtained results, we can safely say that the use of machine learning technologies is justified, since even the base model demonstrated quite satisfactory results.

It is worth noting that lowering the input resolution does not lead to an increase in performance to the extent that the width multiplier does. This fact, in combination with unpredictable changes in accuracy, allows us to conclude that for this kind of objects, manipulations with the input resolution do not make sense.

As for the width multiplier, this parameter has shown itself worthy of attention, since it allows reducing the processing time by up to 6-7 times. Although the accuracy is not directly proportional to this parameter, the potential increase in processing time justifies conducting such an experiment for each new object in order to find the optimal width multiplier.

For the chosen object (pavement tiles), a model with a width multiplier of 0.25 and input resolution of 224×224 is the most optimal. This model demonstrated an average accuracy of 100%, having confidence of 99.93% for only one image, and an average processing time of 0.364 seconds.

MobileNets family of models has demonstrated high accuracy and processing time even on low-end hardware. Therefore, it is able to meet the demand of enterprises for technologies that allow to automate quality control processes and to reduce the cost of production. Further research will be focused on finding the optimal amount of training data for models and exploring their capabilities on other objects.

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