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Deep Learning Method for Classifying Items into Categories for Dutch Auctions

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Artificial Intelligence (AI) methods are widely used in our lives (phones, social media, self-driving cars, and e-commerce). In AI methods, we can find convolutional neural networks (CNN). First of all, we can use these networks to analyze images. This paper presents a method for classifying items into particular categories on an auction site. The technique prompts the seller to which category assign the item when creating a new auction. We choose a neural network with a number of image convolution layers as the best available approach to address this task. All tests were carried out in the Matlab environment using GPU and CPU. Then, the tested and verified solution was implemented in the TensorFlow environment with a CPU processor. Thanks to the cross-validation method, the effectiveness of the recognition system was fully verified in several stages. We obtained promising results. Consequently, we implemented the developed method by adding a new sales offer on the Clemens website.

Keywords: deep learning, internet auction, classification.

1. Introduction

Nowadays, AI methods have become highly prevalent in our lives. We can find these methods in phones, social media, self-driving cars or e-commerce. One of the AI methods is CNN. This class of artificial neural networks is used to analyze images. The most significant advantage of CNNs is that they can automatically identify key features without human supervision. This advantage contributes to their widespread application in various fields [2].

CNNs have also found applications in a variety of industrial fields. Cruz *et al.* presented in [10, 11] one such application. The authors described the welding process of a pressure vessel as one of the most important stages in manufacturing of this vessel. Such a process requires the implementation of proper welding control procedures. These controls are designed to detect defects leading to accidents. In their research, the authors used CNN to detect the misalignment in welded parts.

CNNs have also been used in drone technology. In [20–22], Rojas-Perez and Martinez-Carranza used these networks in the so-called DeepPilot approach. In this approach, camera images serves as input, and flight commands are anticipated and returned as output. The flight commands consist of four elements: the angular position of the drone's body frame in roll and pitch angles, rotational speed in the yaw angle, and vertical speed. The generated commands are then passed on to the aircraft's internal controller. Thanks to this, the drone can navigate autonomously during the flight.

In [15], Kolar *et al.* focused on using a CNN in the construction industry. The authors used CNN to develop a safety railing detection model. During the research, they used the architecture of the Visual Geometry Group with a 16-layer model (VGG-16). Similar methods we can find in [32, 33].

Achour *et al.* in [1] presented the use of CNN in the individual identification and analysis of feeding behavior of farm animals. The authors used four different networks at different stages of the research. They determined four following stages: detecting the presence of dairy cows in the feeding zone, determining the position of the dairy cow in front of the feeder, checking the food availability in the feeder, recognizing the food category, and individual identification of the dairy cow. Other methods used in agriculture we can find in [3, 13].

In [27], Tian *et al.* presented the use of CNN in the meteorological industry. The authors developed a hybrid model to estimate the intensity of a tropical cyclone using satellite remote sensing. Similar research was described in [28] and [29].

In addition, CNNs have gained approval in generating spatial patterns and extract vegetation properties from remote sensing images [12, 14, 19]. Other applications of the CNN that are worth mentioning are: food packaging [5, 18], detection of roller bearings in rotating machines [23, 31], classification of visible surface defects of semiconductor wafers [9, 30], medical applications [4, 16], security protocols [24–26] or waste classification for recycling [6–8].

As part of our project, we have decided to use AI methods in the form of CNN on an online auction site. In this case, AI will assist the users in adding a new item and suggest the category to which the item belongs among the ones available on the website.

The rest of the paper is organized as follows. The second section presents a description of our method. Section 3 presents a description of the environment used during the research. Section 4 presents data characteristics. Section 5 presents the obtained results and data analysis. Section 6 presents the implementation of adding a new sales offer on the Clemens website. In Sec. 7, a summary of our research is presented.

1.1. Acronyms

In Table 1, we present a summary of all this paper's acronyms and their explanation.

Table 1. List of acronyms used in this paper and their explanation.

Acronym	Explanation
AI	artificial intelligence
CPU	central processing unit
FC	fully connected
GPU	graphical processing unit
HOG	histogram of oriented gradients
(R)CNN	(recurrent) convolutional neural network
SIFT	scale-invariant feature transform
SVM	support vector machines
SURF	speeded up robust features
VGG	Visual Geometry Group

2. Description of the method

Our work aims to develop a method for classifying items into particular categories on the auction site. The method prompts the seller to which category to assign the item when creating a new auction. The first assumption was that the method would operate online on the server, with network training executed on a desktop computer.

Upon analyzing the problem we determined that the best available approach to solve this task is to employ a neural network with multiple image convolution layers (i.e., CNN). The stages of developing algorithms based on classic methods using image analysis, such as HOG, SIFT, SURF, SVM, etc., have been omitted due to their susceptibility to changes in lighting conditions. In addition, complex modern neural networks of the CNN type are characterized by built-in feature extraction mechanisms. Therefore, they do not require the use of additional algorithms in this area.

Various available and known architectures and their layer configurations had to be tested. Alexnet, VGG16, VGG19, DarkNet and RCNN architectures were selected for the next research stage. The results shown in Table 2 were achieved

Table 2. The results of preliminary research of the CNN.

Data set	Learning/Validation [%]	Testing [%]
Alexnet	87	77
VGG16	94	90
VGG19	96	93
DarkNet	19	14
RCNN	91	87

at this stage. Table 2 presents accuracy values of learning/validation and testing for the mentioned architectures.

The analysis of the results resulted in selecting the VGG16 and VGG19 networks for further research, the structure of which is shown in Fig. 1. The transfer learning technique was used for further learning. The structure of these networks was adapted to the project's needs, changing the number of outputs to 30 in the last fully connected (FC) tier.

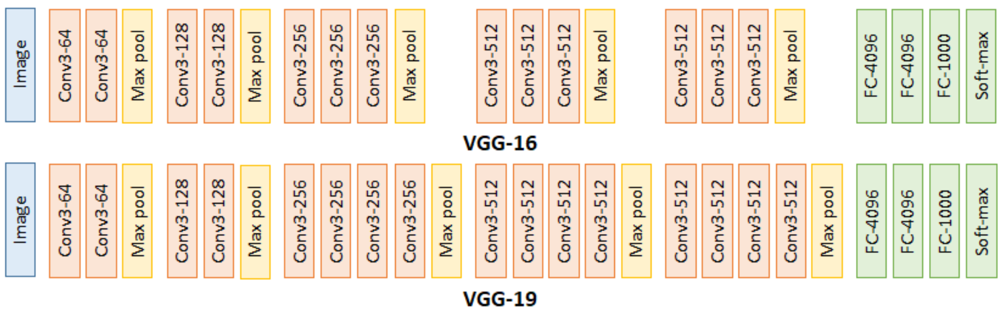

Fig. 1. Structure of VGG-16 and VGG-19 networks.

Transfer learning uses an existing network, learns to solve a similar class of problem, and trains only the last few layers while leaving the remaining parameters (responsible for extracting image features) unchanged. These trained layers may differ in structure from those in the original network, particularly in the last layer, whose number of exits depends on the number of classes to be recognized. Thanks to transfer learning, the network learning time was about several dozen minutes for each case (learning or network parameters) compared to several days required to train the entire network.

In the next step, we used the cross-testing technique because the results obtained using this technique turned out to be the closest to the results of actual tests carried out by users that classified photos into categories.

3. Research environment

Two software tools were used in the research: Matlab and TensorFlow. First, all tests were carried out in the Matlab environment using GPU and CPU, and then the tested and verified solution was implemented in the TensorFlow environment with CPU. It was assumed that network learning would take place off-line on a desktop computer equipped with a high-performance graphics card used for tensor calculations, i.e., with the use of GPU processors (the work involves two workstations each featuring an AMD Ryzen 9 3900X processor 3.8GHz 12 cores, 32 GB DDR4 memory, Samsung 970 EVO Plus 1TB M.2 disk, and ASUS GeForce RTX 2080 Ti ROG STRIX 11GB graphics card). Only a CPU was used on the server, so there was no need to purchase specialized servers equipped with dedicated graphics cards in the target solution.

4. Data characteristics

A database of photos representing items from individual categories was created to verify and analyze the developed method. The collected photos have the following parameters:

- size: 720×480 or 480×720, horizontal or vertical orientation,
- RGB color, 24 bits,
- minimum resolution of 70 dpi,
- the subject stands out from the background and is the focal element,
- only one object is visible in the photo, representing only one category, and the photo shows the entire object.

A total of over 36 000 classified reference photos were obtained, with each of the 30 subcategories having at least 1000 training photos. From this, 200 validation and 200 test photos were randomly selected. Obtaining a balanced number of photos in every category from Internet sources was possible during data acquisition.

The full list of categories and the corresponding number of photos in each category are shown in Table 3.

5. Results and data analysis

Cross-validation is a statistical method that divides a statistical sample into subsets and then performs all analyses on some of them (training set). In contrast, the other sets are used to confirm the reliability of the results (test set and validation set). Thanks to this method, the effectiveness of the recognition system can be fully verified in several stages because the tests use data other

Table 3. List of categories and number of photos.

Number	Category	Number of photos
1	photography	1540
2	graphics	1200
3	painting	1200
4	maps	1050
5	posters	1100
6	bronzes	1434
7	icons	1250
8	sculptures	1100
9	ceramics	1014
10	minerals	1005
11	porcelain	1350
12	clocks	1100
13	silver	1100
14	glass	1115
15	fabrics	1000
16	banknotes	1000
17	numismatics	1500
18	philately	1058
19	bibliophilia	1160
20	orders	1000
21	militaria	1037
22	postcards	1350
23	model making	1700
24	electronics	1200
25	jewellery	1250
26	stones	1037
27	watches	1425
28	furniture	1500
29	lighting	1400
30	mirrors	1000
	Total	36 175

than for learning, and K-fold validation is employed, in which the set is divided into K subsets, where $K = 5$. Then, each subset is successively taken as the test set, while the remaining subsets form the training set. The analysis is then performed K times, and the K results are averaged to produce a single result. The results obtained with this method closely align with the results obtained from real tests executed by real users who classified photos into categories.

The entire set of photos selected for analysis consisted of 30 classes, with at least 1000 photos in each class. The images were multiplied by applying geometric transformations: reflection and rotation. As a result, we obtained 10 000 photos for each category. Subsequently, each class was divided into five parts – randomly. Five data containers A, B, C, D and E were created in the next step. In container A, the first subset in each class (2000 photos) was used as test data, and the remaining data were employed for training and validation (6000 – training, 2000 – validation). In the next container B, the second subsets were used to test the remaining data, and in the next containers, the same was conducted. The learning parameters determined in the course of the analyses were finally as follows:

- Initial Learn Rate: 0.001,
- Learn Rate per Period: 10,
- LearnRateDropFactor: 0.1,
- LearnRateDropPeriod: 5,
- MaxEpochs: 7,
- MiniBatchSize: 64,
- Regularization: 0.1.

Individual images were randomly assigned to the test set, and each image was assigned to the test set only once. Thanks to this, we obtained a reliable test results (we train with different images and test with others). The results of these tests are shown in Tables 4 and 5.

Table 4. The results of VGG-16 network.

Data set	Learning/Validation [%]	Testing [%]
A	92	81
B	93	90
C	92	90
D	93	89
E	92	83
average	92.4	86.6

Table 5. The results of VGG-19 network.

Data set	Learning/Validation [%]	Testing [%]
A	92	82
B	92	89
C	93	90
D	92	87
E	91	86
average	92.4	86.6

Figures 2 and 3 show the research results in the form of a confusion matrix for each network.

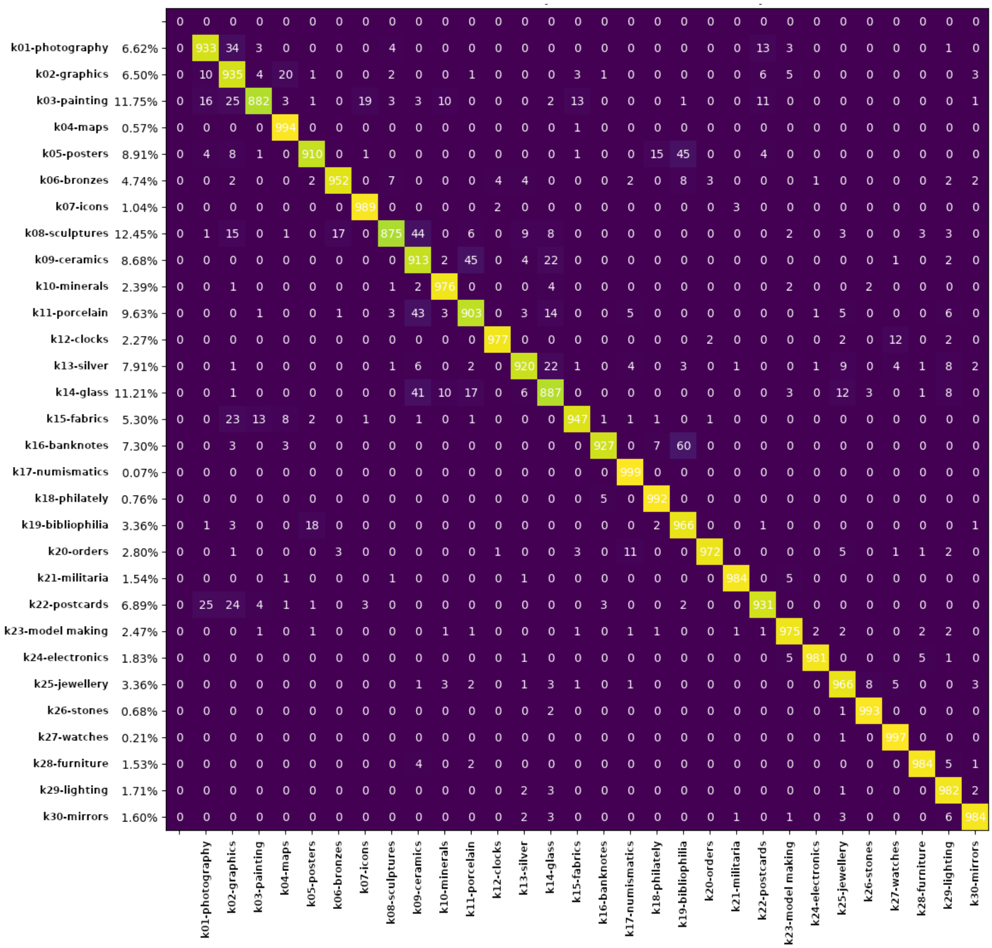

Fig. 2. Confusion-matrix for VGG-16 network.

The best recognition results were obtained for the following categories: numismatics (recognition error for VGG-16 and VGG-19, respectively – 0.07% and 1.87%), electronics (0.58% and 1.83%), icons (0.80% and 1.84%), philately (error 0.47% and 2.27%). Good results were obtained for orders (1.60% and 2.80%), mirrors (1.30% and 2.5%) and militaria (1.35% and 2.41%).

The highest level of recognition errors was obtained for the following categories: ceramics (VGG-16 and VGG-19, respectively – 8.68% and 18.64%), porcelain (9.63% and 17.19%), graphics (6.50% and 20.92%), painting (6.58% and 17.50%), glass (6.46% and 13.45%). There was a problem distinguishing be-

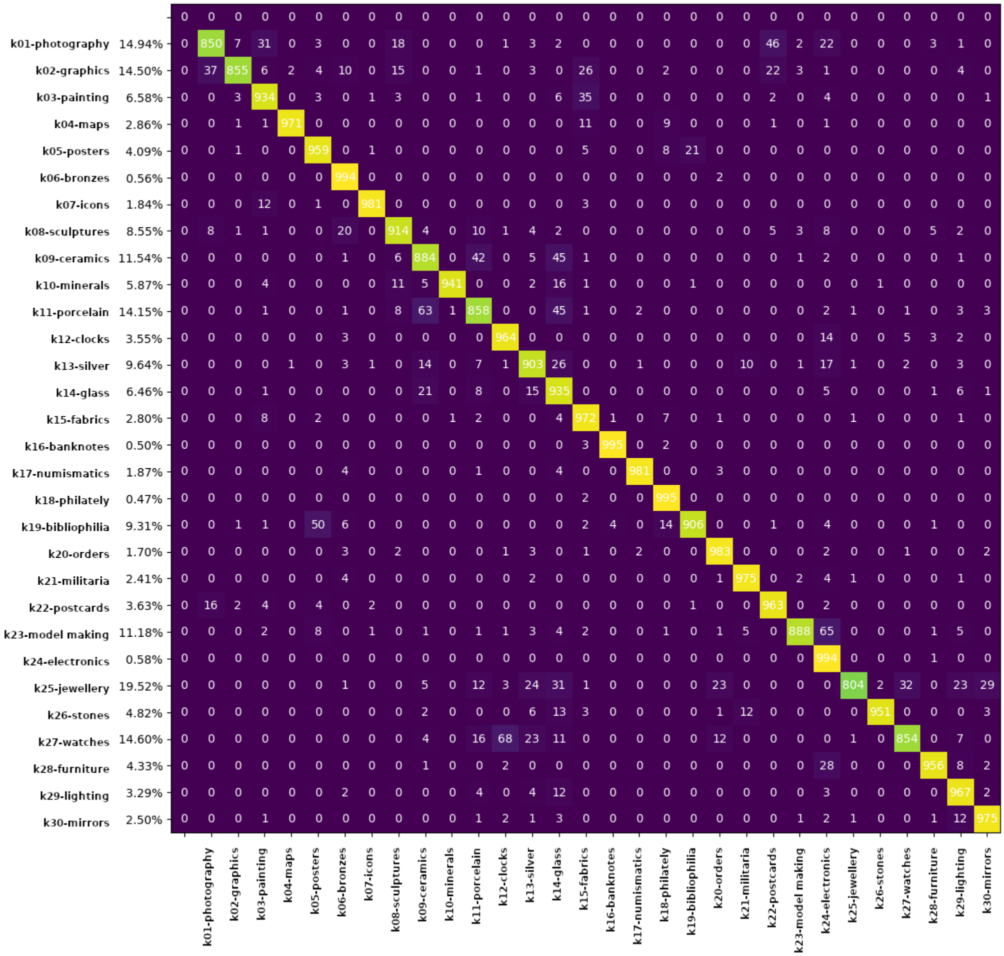

Fig. 3. Confusion-matrix for VGG-19 network.

tween ceramics, porcelain, and sometimes glass. This is due to the properties of the materials from which the items are made. Therefore, the target system can combine these categories into one and reduces the error rate.

6. Implementation

The developed method was implemented in the form of adding a new sales offer on the Clemens website [17]. An appropriate layer of data presentation and communication with users as part of this functionality was created. The process of uploading the photo is the first step a seller needs to take to add a new sale offer. After loading the first image, the following message appears: “Based on the main image, an artificial intelligence (AI) system has tried to detect the item category. Did it make the right choice?".

Below this message is a list of suggested categories and subcategories where the seller should place the offer for sale. According to the algorithm, the first line is the most likely category and subcategories. Each suggested category has a button "Yes, set this category". By clicking this button, the seller confirms that the suggested category has been indicated correctly and that this category and subcategory of the item are automatically completed in the form. This also includes a detailed category (see Fig. 4).

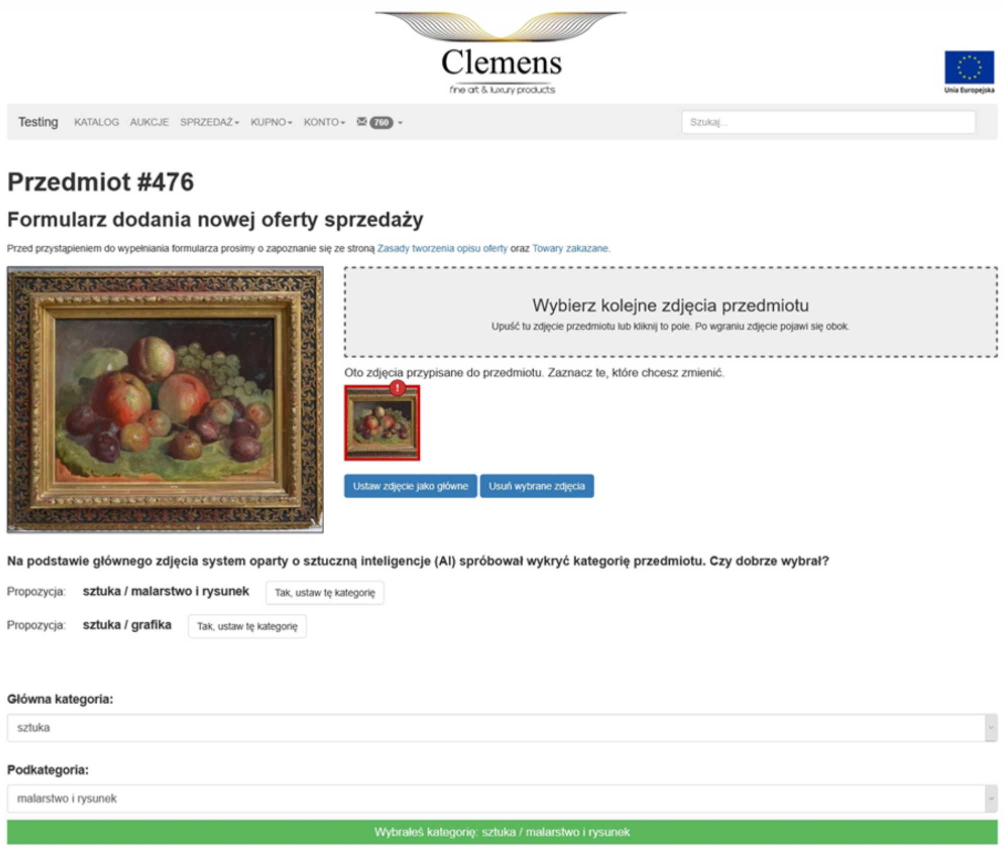

Fig. 4. Clemens portal.

7. Conclusion

In this paper, we presented our project, which aimed to develop a method for classifying items into particular categories on an auction site. The method prompts the seller to assign the appropriate category to the item when creating a new auction. We assumed that while the method operated online on the server, the network training took place on a desktop computer. We decided to use AI methods in the form of the CNN on the online auction site. In this case, AI assists users in adding a new item and suggests the category to which the item belongs among those available on the website.

As part of the research, the implementation of the online prototype was completed. This prototype has a modular structure. The implemented modules include testing for photo format, sharpness, contrast, the presence of artefacts and signs, as well as category prediction. We properly tested the prototype operation, and our results are promising. We intend to develop the implemented prototype with new functionalities in future research.

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