Grzegorz Mazurek, Małgorzata Durlej, Juraj Šrámek
Structure and Environment 2023, vol. 15, (3), pp. 159-167, Article number: el 014
https://doi.org/10.30540/sae-2023-014

Structure and Environment
ISSN 2081-1500
e-ISSN 2657-6902
https://content.sciendo.com/sae
https://sae.tu.kielce.pl

sciendo

Kielce University of Technology

DOI: 10.30540/sae-2023-014

APPLICATION OF DEEP LEARNING TECHNIQUES IN IDENTIFICATION OF THE STRUCTURE OF SELECTED ROAD MATERIALS

ZASTOSOWANIE TECHNIKI GŁĘBOKIEGO UCZENIA DO IDENTYFIKACJI STRUKTURY WYBRANYCH MATERIAŁÓW DROGOWYCH

Grzegorz Mazurek*, Małgorzata Durlej
Kielce University of Technology, Poland
Juraj Šrámek
University of Zilina, Slovakia

Abstract

In research, there is a growing interest in using artificial intelligence to find solutions to difficult scientific problems. In this paper, a deep learning algorithm has been applied using images of samples of materials used for road surfaces. The photographs showed cross-sections of random samples taken with a CT scanner. Historical samples were used for the analysis, located in a database collecting information over many years. The deep learning analysis was performed using some elements of the VGG16 network architecture and implemented using the R language. The learning and training data were augmented and cross-validated. This resulted in the high level of 96.4% quality identification of the sample type and its selected structural features. The photographs in the identification set were correctly identified in terms of structure, mix type and grain size. The trained model identified samples in the domain of the dataset used for training in a very good way. As a result, in the future such a methodology may facilitate the identification of the type of mixture, its basic properties and defects.

Keywords: deep learning, tomograph, R programming language, classification, road surfaces, correlation, digital image

Streszczenie

W badaniach naukowych obserwuje się coraz większe zainteresowanie wykorzystaniem sztucznej inteligencji do poszukiwania rozwiązań trudnych problemów naukowych. W niniejszym artykule został zastosowany algorytm głębokiego uczenia z użyciem obrazów próbek materiałów wykorzystywanych do budowy nawierzchni drogowych. Fotografie przedstawiały przekroje losowych próbek wykonane za pomocą tomografu komputerowego. Do analizy wykorzystano próbki historyczne, znajdujące się w bazie danych zbierającej informacje z wielu lat. Analizę głębokiego uczenia wykonano przy użyciu niektórych elementów architektury sieci VGG16 i zaimplementowano, stosując język R. Dane uczące oraz treningowe poddano augmentacji oraz walidacji krzyżowej. W rezultacie uzyskano wysoki poziom 96,4% jakości identyfikacji rodzaju próbki oraz jej wybranych cech strukturalnych. Fotografie w zbiorze identyfikacyjnym zostały poprawnie zidentyfikowane pod względem struktury, typu mieszanki oraz uziarnienia. Wytrenowany model w bardzo dobry sposób zidentyfikował próbki w obszarze dziedziny trenowanego zbioru danych. W rezultacie taka metodyka może w przyszłości ułatwić identyfikację rodzaju mieszanki, jej podstawowych właściwości oraz defektów.

Słowa kluczowe: głębokie uczenie, tomograf, język programowania R, klasyfikacja, nawierzchnie drogowe, korelacja, obraz cyfrowy

*Kielce University of Technology, Poland, e-mail: gmazurek@tu.kielce.pl

1. INTRODUCTION

Mineral-asphalt composites are used in the design of new road surface structures, but so are other cement-bonded materials [1]. Among these, recycled materials using both asphalt binder and cement have their well-deserved place [2]. These are materials used in deep recycling technology. Each of these materials has a different structure. It is mainly due to the presence of different aggregates as well as the way the mastic or mortar phase is shaped. Deep recycling technology is definitely dominated by recycled aggregate (RAP) [3]. In contrast, mineral and asphalt mixtures (mma) are dominated by crushed aggregate, with a crushing coefficient of $C_{90/3}$, which is required primarily to ensure that the mma has an adequate internal friction coefficient. In contrast, cement-bound mixtures for substructures as well as soil-cement stabilisations have a structure similar to cement concrete [4] taking into account the macrostructure of the pavement layers, which are made of heterogeneous materials. The interaction between the joined layers was determined by applying a cohesion contact model. The parameters of the model were identified using the results obtained in the course of the actual Leutner tests. The heterogeneity of the structure was mapped based on a digital image of a tomographic cross-section. The separation of the materials included in the individual layers was performed with the use of a script in the MatLab program. Thanks to this, the batch file for the Abaqus program was prepared thoroughly. As a result, it was possible to map as closely as possible the profile of the deformation caused by the loss of the interlayer adhesion. Based on the data analysis, it was found that in the layer of the base course constructed from cold-applied recycled materials, the loss of interlayer adhesion is related to the state of non-linear mastic deformation. As a consequence, it was found that large deformations in the mastic structure would cause losses of aggregate grains in the recycled layer. In addition, a large horizontal displacement within the layer of the base course made of recycled material is one of the likely causes of edge fractures in the road structure.","container-title":"Structure and Environment","DOI":"10.30540/sae-2021-011","ISSN":"20811500","issue":"4","journalAbbreviation":"SAE","source":"DOI.org (Crossref. These differences suggest that it is possible to find relationships from which a preliminary diagnosis can be made in terms of material quality as well as potential defects in the structure.

To some extent, this problem can be solved by using shallow machine learning techniques. Such data mining techniques (Data Mining) are so far applied, but they are mainly used to correctly predict the mechanical or physical properties of road materials. The undoubted advantage of Data Mining methods is the inclusion of both qualitative and quantitative variables. In their paper, Rebelo et al. [5] used a number of DM techniques to effectively predict the water resistance of mineral-asphalt mixtures. Whereas in the paper [6] the authors have used DM to improve road surface rutting resistance. In their work, Guo and Hao [7] used a random forest algorithm to assess road surface durability using information on emerging damage. The estimation of the stiffness modulus was successfully determined using Falling Weight Deflectometer (FWD) and with the aid of an artificial neural network (ANN) or support vector machines (SVM) [8, 9]. DM techniques have also excelled in predicting IRI [10] however, limit the implementation of ML by practitioners and transportation agencies. One of these challenges is related to the high variability in the performance of ML models as reported by different studies and the lack of quantitative evidence supporting the true effectiveness of these techniques. The objective of this paper is twofold: to assess the overall performance of traditional and ML techniques used to predict pavement condition, and to provide guidance on the optimal architecture and minimum sample size required to develop these models. This paper analyzes three ML algorithms commonly used to predict International Roughness Index (IRI) or skid resistance [11].

However, the best technique to solve this complex problem that is beyond the perception of the observer's senses is deep learning using convolutional networks. At the present time, this type of analysis is being successfully used especially in medical diagnostics [12]. Nevertheless, it also finds use in civil engineering. The road industry has recently seen the emergence of preliminary analyses using deep learning to identify the condition of road surfaces. This approach makes it easy to identify damage and perform a quick classification of road surface condition "on the fly" by analysing images taken with a smartphone [13]. It can also support the identification of particularly damaged sections of road surface [14]. However, it should be made clear that it is difficult to find attempts in the literature to use a deep learning (DL) algorithm to recognise the structure of road materials from tomograph-derived images. The level of abstraction of the input data suggests that other methods will not be effective for the intended purpose. The search for similarities through image decomposition requires the consideration of several million indeterminates, which clearly disqualifies an analytical approach using, for example: logistic regression or DM. An additional advantage of using DL is that it not only looks for similarities in the contours of objects, but also for changes in their colour.

The aim of the research and analysis performed was to determine the scale of the feasibility of implementing DL to identify the structure of selected road materials. The paper also considers the possibility of looking for correlative relationships between the identified objects and selected physical characteristics of road composites. This article should be regarded as a feasibility study of the implementation of a current state-of-the-art learning technique for road applications.

2. MATERIALS AND METHODS

2.1. Deep learning

As already mentioned, a technique frequently used for classification and regression tasks is the shallow learning technique. With its help, a number of scientific problems can be solved. However, in order to do this, steps must be taken to process the features, i.e. to create appropriate layers of data representation. In deep machine learning, this step is automated. This facilitates the entire workflow and is therefore most suitable for processing complex objects such as digital images.

Deep learning involves the application of multiple successive layers of representation. This is a technique that works very well when working on perceptual tasks. In the case of shallow learning, the addition of subsequent steps leads to less and less improvement in the results obtained [17]. This is because the optimal first layer of the representation is not the optimal layer of the multilayer model. In deep learning, it is possible to combine all layers of data representation. In other words: modifying one internal feature of the model results in automatic adaptation of the entire model without the need for user intervention. This change is controlled by a single feedback signal. For shallow machine learning models, it is not possible to correctly describe multiple relationships in objects with a high level of abstract representation without the need to add subsequent intermediate layers (independent of each other).

At the present time, deep learning involves the creation of dozens of successive representations learned from training data, compared to shallow learning which usually contains two layers of representations. Although deep learning was developed for classification tasks involving object-image mapping using a deep sequence of simple transformations, the DL technique can be used successfully for regression tasks. The issue that needs to be changed is a different algorithm for tuning the weights, i.e. the optimiser, and a different form of the objective function (loss function). A loss function is nothing more than the distance between the predicted value and the actual value. In the case of an image, it denotes the accuracy of the image processing by the network. Far more important is the selection of the optimiser, i.e. the backpropagation algorithm. It is directly responsible for the efficiency in tuning the weights of the transformation function which directly translates into the efficiency of the representation of the output results. As a result, the operation of the deep learning algorithm can be represented by the nomogram in Figure 1.

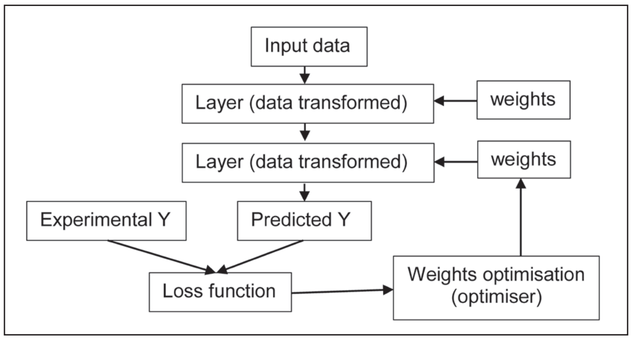


Fig. 1. Convolution network diagram

A network with minimal loss can be considered trained, which translates into a high representation of the test object. In essence, DL can be thought of as a multi-stage operation of "distilling" information passing through successive "filters", producing increasingly clear and homogeneous results. The key to achieving high efficiency is proper management of the weights (Fig. 1). The weights are a set of numbers that allow the data transformation to be performed in such a way that the process of mapping predicted data sets to experimental ones is as accurate as possible. Therefore, in deep learning, a network can contain millions of parameters. A key element that has made DL techniques more affordable is the availability of efficient optimisers and the calculational capacity of numerical machines. The calculation time involved in fine-tuning the weights is fast and the efficiency is far better than traditional methods such as logistic regression.

2.2. Convolutional network architecture

This paper uses elements of the VGG16 convolutional network architecture trained on the ImageNet set [18]. The ImageNet set included 1.4 million images divided into 1,000 classes. The present network was trained on a very general set and had a correctness of object identification of >96%. Thus, the learned spatial hierarchy of features can effectively form the basis for identifying the structure of road materials assigned to classes not included in the ImageNet set. The ability to transfer the "knowledge" contained in pre-trained networks to other sets is a huge advantage over shallow learning methods. The VGG16 network was used for the analysis using the technique of extraction of features of interest. These features are then processed by a new classifier, which in this paper will be subjected to a process of training from scratch. This network will consist of pooling and convolution layers. The final stage is the densely connected classifier mentioned earlier. Indeed, the convolutional part of the network consists of the overall rule and image recognition concepts. The convolutional part can be shared, while the dense classifier is directly related to the specifics of the object, in this case a photograph taken via a road material tomograph.

Given the above assumptions, the concept and architecture of a trained convolutional network will be used, applying a feature extraction technique in the process. A new final classifier will then be trained from scratch. The use of the VGG16 trained convolutional network will allow the use of generalisations in image interpretation that have proven successful for identifying ImageNet set objects. The abbreviated architecture of the VGG16 network is given below (Table 1).

Table 1. Abbreviated form of the convolutional architecture of the VGG16 network

Layer (type)	Output Shape	Param#
Input_1 (InputLayer)	(None, 150,150,3)	0
block1_conv1 (Conv2D)	(None, 150,150,64)	1792
block1_conv2 (Conv2D)	(None, 150,150,64)	36928
block1_pool (MaxPooling2D)	(None, 75,75,64)	0
(…)		
block5_conv1 (Conv2D)	(None, 9,9,512)	2359808
block5_conv2 (Conv2D)	(None, 9,9,512)	2359808
block5_conv5 (Conv2D)	(None, 9,9,512)	2359808
Block5_pool (MaxPooling2D)	(None, 4,4,512)	0
Total params: 14,714,688 Trainable params: **14,714,688**		

The final feature map of the VGG16 network to be used for further analysis was (4,4,512). The next step was to extend the model, as previously conceived, to include dense classifier layers. The downside of this procedure is the long costly calculation time, which depends on the performance of the processor. On the other hand, an indisputable advantage of this technique is the use of "data augmentation", which is essential when there is a small input data set. The problem presented in this paper was solved using a sequential model, linking successive network layers. The final network model was as follows (Table 2).

Table 2. Abbreviated form of the convolutional architecture of the VGG16 network

Layer (type)	Output Shape	Param#
VGG 16 (previous model)	(None, 4, 4, 512)	1,471,4688
Flatten_1 (Flatten)	(None, 8192)	0
dense_3 (Dense)	(None, 256)	2,097,408
dense_4 (Dense)	(None, 1)	257
Total params: 16,812,353 Trainable params: **16,812,353**		

The added dense classifier required to obtain a measurable value for the class similarity scale of a given photograph introduced an additional 2 million parameters over the baseline VGG16, so the final model included a total of more than 16 million parameters. Therefore, the process of training the network had two-stages. Initially, it was necessary to freeze the VGG16 network for the duration of the dense classifier training. In the next stage, part of the VGG16 network blocks were unfrozen. This will provide greater control over the changes in the "knowledge" that the VGG16 convolution network brings.

2.3. Examination by means of computed tomography

Computed tomography is a non-destructive technique used to analyse the internal structure of materials based on the properties of X-rays. One of these properties is the ability to travel through matter, losing energy on the way according to Beer's law. The incidence of linear attenuation μ depends on the density of the material under examination at each point through which the beam passes. The creation of a tomographic image is based on measuring the absorption of radiation by an object. Performing a scan in a CT scanner is based on directing a beam of X-rays at an object and then recording its intensity through a detector on the other side of the object.

The study uses a composite of object projections taken from different directions to generate two-dimensional (2D) cross-sectional images and then three-dimensional (3D) models. The scanned object is divided into small cells, called voxels (*volumetric element*, equivalent to a pixel for a 2D image), for which the linear absorption coefficient is the same. A the tomograph operating diagram is shown in the figure below (Fig. 2).

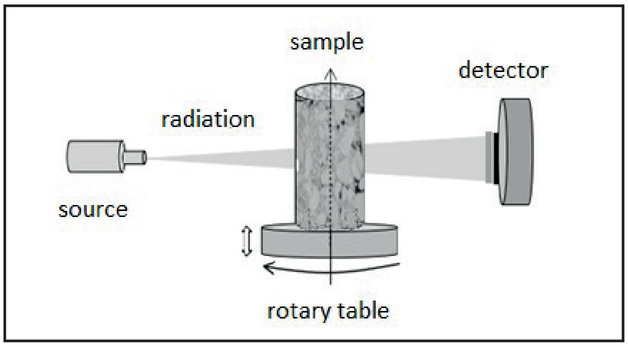


Fig. 2. Tomograph operating diagram [19]

Scanning is performed by exposing the object to X-rays while rotating the sample 360° relative to a stationary tube and detector. The accuracy of the final representation depends on the number of projections made during the object's rotation. By having projection images for multiple cross-sections of the object, the image of the entire sample is reconstructed using the Radon transform. The practical result is a three-dimensional greyscale image in which each shade of grey corresponds to a specific density value. Lighter tones represent higher densities, while darker tones denote lower density materials.

The study was performed on a Nikon XT H 225 ST CT scanner. A rotating lamp generating a beam of radiation with a maximum voltage of 225 kV and a power of 450 W was used. When performing the scans, the voltage and intensity values used were selected experimentally, by scanning the sample several times, to ensure the best possible parameters for the type of material. From the combination of almost 4,500 images, a 3D model of the object with a resolution of at least 84 µm was created. This was achieved by reconstructing the data and pre-processing it, determining the axis of rotation, reducing noise, sharpening edges and applying filters in CT Pro 3D.

2.4. Research sample

The set of photographs of the various materials used for incorporation into the road structure included 260 photographs. All photographs were divided into 14 classes. Each class represented one object with characteristics that differed from each other. The following types of road materials found in the archival research database constituted the set of selected objects (Table 3).

Table 3. Identification and description of object classes

No.	Class	Description
1.	CC(G)	Cement concrete 0/16 containing, among other things, granite aggregate
2.	AC11(Ga)	0/11 asphalt concrete containing, among other things, gabbro aggregate
3.	WMS_I	0/16 asphaltic concrete with a high stiffness modulus with limestone aggregate.
4.	MCAS_I	Recycled mix of foamed asphalt with a fine-grained structure with the addition of road binder C5 [20]
5.	AC16_PMB	Asphalt concrete 0/16 containing modified asphalt for the wearing course
6.	AC22P	Asphalt concrete for sub-base with a maximum grain size of 22 mm
7.	WMS_II	0/16 asphalt concrete with a high stiffness modulus
8.	AC8S	Asphalt concrete with a grain size of 0/8 for the wearing course
9.	MCE	Cement & emulsion mixtures for incorporation into the sub-base layer in deep recycling technology
10.	MMP	0/16 mm mineral-emulsion-polymer mix with dispersed powders
11.	MCAS_II	Recycled mix with foamed asphalt containing limestone aggregate
12.	CBGM_CEMI	A soil-cement mixture designed for a sub-base layer with a cement content of 4%
13.	CBGM_CEMI_M	A soil-cement mixture containing metakaolin designed for an auxiliary sub-base layer with a cement content of 4%
14.	CBGM_PK	A soil-cement mixture containing bark ash designed for an auxiliary sub-base layer with a cement content of 4%

The sample set was randomly divided into two subsets with the following percentages:

- learning – 70%,
- test – 30%.

In addition, an additional set of photographs with similar characteristics to the learning set was used for validation to confirm the validity and effectiveness of the DL technique used. A subset of the learning data was selected so that the number of data in the classes and their types were as equivalent as possible.

3. ANALYSIS OF RESEARCH RESULTS

3.1. Data set augmentation

The dataset used in the analysis is not large in number, so the learning effect was enhanced by using a data augmentation technique. It consists of randomly transforming a random image in such a way as to best eliminate certain peculiarities and its initial settings and thus enhance the level of generalisation of the trained convolutional network. This procedure dismisses the possibility of fine-tuning the scales using two of the same photographs, i.e. it prevents the network from "overlearning". A code snippet with the configuration of the parameters used during data augmentation is shown below:

```
train_datagen_augmentation<- image_data_generator(
rescale=1/255,
rotation_range = 40,
width_shift_range = 0.2,
height_shift_range = 0.2,
shear_range = 0.2,
zoom_range = 0.2,
horizontal_flip = TRUE,
fill_mode = "nearest").
```

In summary, data augmentation is not about creating new data. Its task is to use existing photographs submitted for further analysis by performing a random and one-off transformation in them.

3.2. Course of the learning process

The first stage of the convolutional network learning process started by freezing the weights of the VGG16 network. In this step, only the dense classifier weights were trained. Otherwise, the training process could introduce permanent changes to the underlying convolutional network VGG16, strong enough that the resulting network would generate incorrect results. The loss function should be selected according to the scale of the problem. Therefore, a categorical crossentropy function was used. It is an optimisation function that classifies data by predicting the probability of the data belonging to one of the defined classes. On the other hand, a softmax function was used as the last class activation function together with an RMSprop optimiser with a learning rate of $1 \cdot e^{-5}$. The final result was a vector of probability values for assigning a given object to all 14 classes in the range <0;1>. In the first stage, 200 epochs were used, taking a batch of 20 photographs at a time for analysis. The result of the trained network, through the use of a validation set, achieved a concordance expressed by a coefficient of determination of $R^2 = 92.9\%$ with a value of the loss function of the learning set equalling 2.0086 and, respectively, of the test set equalling 2.0413. An increase in the value of the loss function on the test set suggested a slight overlearning of the network. Thus, further training of the dense classifier did not provide new quality (knowledge) in photograph identification. The results of the test photograph match probability are shown in Figure 3.

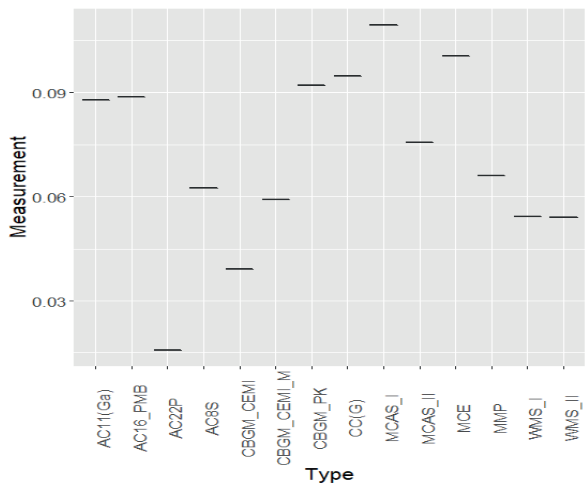


Fig. 3. Probability of an AC16W reference sample photograph belonging to a class of a trained convolutional network

Observing the results in Figure 3, it should be noted that the trained dense classifier and the frozen weights from the ImageNet set found the AC16W asphalt concrete mix similar to the MCAS_I mix (11%) or the MCE mix (10%). This is an unsatisfactory and erroneous result and further fine-tuning of the convolution network is required. This is because originally the scales in the VGG16 network architecture were used to identify objects other than road materials.

Therefore, a second phase related to the fine-tuning of the convolutional network was realised. As a result, the layers of the convolutional network were unfrozen starting from level 3 of the network shown in Table 1. Training took place, introducing another 100 epochs. This value has been set so as not to cause overtraining of the network. Once the training process was complete, the tuned model was validated by assessment of its effectiveness, using a validation set of the same model used in the first step. The effectiveness of the model, as expressed by the R^2 coefficient for the model, was 96.4%. This result should be regarded as very good. Such efficiency should be linked directly to the unfreezing of the network layers responsible for recognising high-level detail. The improvement in the quality of the trained network increased from R^2 = 92.9% (stage 1) to R^2 = 96.4% (stage 2). Nevertheless, a tendency of the network to learn "by heart" was observed in the second phase of network training. This phenomenon is shown in Figure 4.

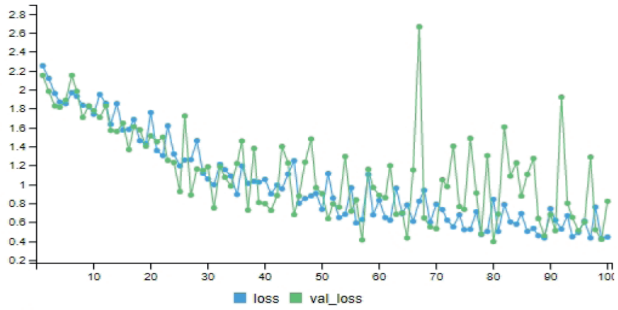


Fig. 4. Graph of the change in the loss function for the learning (loss) and test set data (val_loss)

A negligible increase in error on the test set was observed from epoch 70 onwards, while error stabilisation was observed for the learning set. In order not to cause excessive network overlearning, the number of 100 epochs should not be increased.

3.3. Validation of Results

Validation of the resulting model was subject to an assessment of the ability to identify objects (road materials) that had not been involved in previous model evaluations. Additional validation objects included photographs of the AC16W mix. The result of the AC16W classification against the defined classes is shown below (Fig. 5).

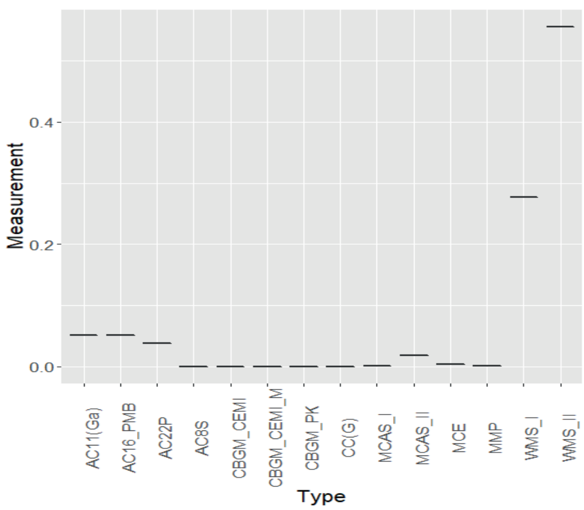
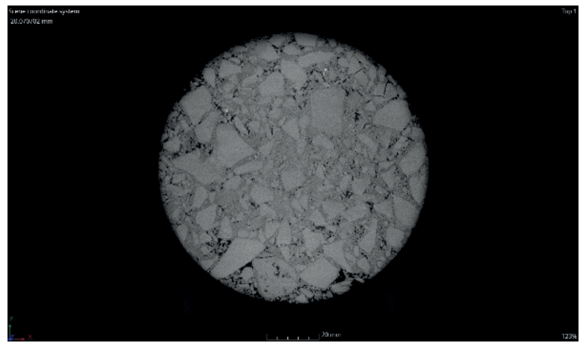


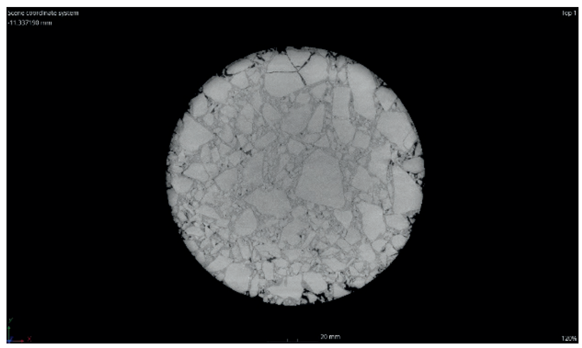
Fig. 5. Probability of the photograph of the AC16W reference samples belonging to the class of trained convolutional networks after stage two (unfreezing of selected layers)

The results of the classification by means of the trained convolutional network, shown in Figure 4, indicate that the greatest similarity of AC16W can be attributed to the WMS_I and WMS_II mix type class. This is definitely a big difference from the phase 1 results (Fig. 3). This time, the algorithm correctly indicated that the analysed samples have a concrete-type closed structure. The DL algorithm firmly disqualified recycled mixtures (MCAS/MCE) and CBGM. To give an idea of the possibility of comparison, photographs of the two mma most similar to the AC16W are juxtaposed in Figure 6.

a)

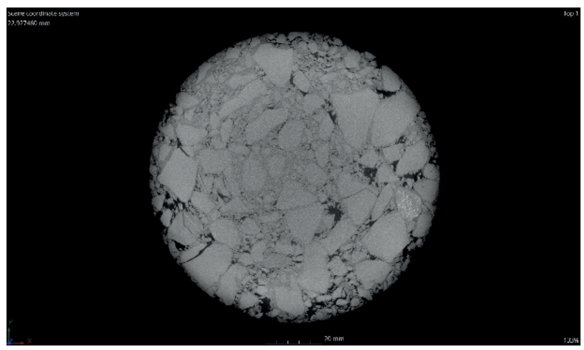


b)



Similarity = 27.7%

c)



Similarity = 55.6%

Fig. 6. Juxtaposition of the two samples with the highest similarity to the reference sample: a) reference sample AC16W, b) WMS_I, c) WMS_II

Probably the rules of similarity established by the convolution network resulted from the nature of the mastic structure produced, the type of aggregate (grey shade) and the pore content. In addition, the grain size, i.e. the dimension of the maximum grain, can also be expected to have made a difference. In the cases analysed (Fig. 6) the grain size curve was 0/16. It turned out that the convolutional network can, with a small set, correctly classify objects with significantly different embedding technology. CBGM and recycled MCE/MCAS mixes are used for the substructure. On the other hand, type WMS or classic AC with concrete structure are used for the upper structural layers. In view of the facts cited, a measurable probability value can be linked to physical characteristics in the future, e.g.: water resistance of the mma.

In the future, it is planned to superimpose heat maps [21], which will allow the key area of the convolutional network to be highlighted, from which it can be determined what caused the sample to be classified in this way. Thus, it will be possible to identify areas in the structure of the material used in road construction which should be analysed in detail, focusing on the reasons for a particular regularity in its structure.

4. CONCLUSIONS

Based on the research and analysis performed, the following conclusions were formulated:

- the use of convolutional network algorithms is an excellent tool for classifying abstract objects of a perceptual nature;
- the use of modifications to the available architecture of other convolutional networks allowed the correct identification of the composite in terms of grain size, type, manufacturing technology and structure;
- the use of data augmentation and the unfreezing of the deep layers of the convolutional network dramatically increased the ability to identify objects from R2 = 92.9% to R2 = 96.4%;
- based on the set of photographs, the network, with a level of concordance of R2 > 96%, correctly classified the AC16W as regards structure, mix type, grain size and colour of the aggregate.

REFERENCES

[1] *Katalog typowych konstrukcji nawierzchni podatnych i półsztywnych*. 2014.

[2] Mazurek G., Buczyński P., Mackiewicz P., Iwański M.: *Field investigation of a deep recycled base course layer containing dedicated three component hydraulic and bituminous binder*, Construction and Building Materials, t. 390, s. 131685, sie. 2023, doi: 10.1016/j.conbuildmat.2023.131685.

[3] Wirtgen Group, *Cold Recycling Technology*, First edition. Windhagen: Wirtgen GmbH, 2012.

[4] Mazurek G., Durlej M., Iwański M., *Numerical modelling of interlayer adhesion in the layer of recycled material with the use of the leutner apparatus and computed tomography scanning*", SAE, t. 13, nr 4, grudz. 2021, doi: 10.30540/sae-2021-011.

[5] Rebelo F.J.P., Martins F.F., Silva H.M.R.D., Oliveira J.R.M., *Use of data mining techniques to explain the primary factors influencing water sensitivity of asphalt mixtures*, Construction and Building Materials, t. 342, s. 128039, sie. 2022, doi: 10.1016/j.conbuildmat.2022.128039.

[6] Gong H., Sun Y., Mei Z., Huang B.: *Improving accuracy of rutting prediction for mechanistic-empirical pavement design guide with deep neural networks*, Construction and Building Materials, t. 190, s. 710-718, lis. 2018, doi: 10.1016/j.conbuildmat.2018.09.087.

[7] Guo X., Hao P.: *Using a Random Forest Model to Predict the Location of Potential Damage on Asphalt Pavement*, Applied Sciences, t. 11, nr 21, p. 10396, lis. 2021, doi: 10.3390/app112110396.

[8] Fakhri M., Dezfoulian R.S.: *Pavement structural evaluation based on roughness and surface distress survey using neural network model*, Construction and Building Materials, t. 204, s. 768-780, kwi. 2019, doi: 10.1016/j.conbuildmat.2019.01.142.

[9] Gopalakrishnan K., Agrawal A., Ceylan H., Kim S., Choudhary A.: *Knowledge discovery and data mining in pavement inverse analysis*, Transport, t. 28, nr 1, s. 1-10, mar. 2013, doi: 10.3846/16484142.2013.777941.

[10] Bashar M.Z., Torres-Machi C.: *Performance of Machine Learning Algorithms in Predicting the Pavement International Roughness Index*, Transportation Research Record, t. 2675, nr 5, s. 226-237, maj 2021, doi: 10.1177/0361198120986171.

[11] Tong Z., Gao J., Sha A., Hu L., Li S.: *Convolutional Neural Network for Asphalt Pavement Surface Texture Analysis: Convolutional neural network*, Computer-Aided Civil and Infrastructure Engineering, t. 33, nr 12, s. 1056-1072, grudz. 2018, doi: 10.1111/mice.12406.

[12] Tran K.A., Kondrashova O., Bradley A., Williams E.D., Pearson J.V., Waddell N.: *Deep learning in cancer diagnosis, prognosis and treatment selection*, Genome Med, t. 13, nr 1, s. 152, grudz. 2021, doi: 10.1186/s13073-021-00968-x.

[13] Arya D. et al.: *Deep learning-based road damage detection and classification for multiple countries*, Automation in Construction, t. 132, s. 103935, grudz. 2021, doi: 10.1016/j.autcon.2021.103935.
[14] Jóźwiak Z., Pożarycki A., Górnaś P.: *Diagnostyka nawierzchni drogowej przy zastosowaniu metod sieci neuronowych – studium przypadku*, Drogownictwo, t. 2, nr 3, s. 65-72, 2022.
[15] Freund Y., Schapire R.E.: *A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting*, Journal of Computer and System Sciences, t. 55, nr 1, pp. 119-139, sie. 1997, doi: 10.1006/jcss.1997.1504.
[16] Nazemi M., Heidaripanah A.: *Support vector machine to predict the indirect tensile strength of foamed bitumen-stabilised base course materials*, Road Materials and Pavement Design, t. 17, nr 3, pp. 768-778, lip. 2016, doi: 10.1080/14680629.2015.1119712.
[17] Chollet F., Allaire J.J., Matuk K.: *Deep learning: praca z językiem R i biblioteką Keras*. Gliwice: Helion, 2019.
[18] Simonyan K., Zisserman A.: *Very Deep Convolutional Networks for Large-Scale Image Recognition*, 2014, doi: 10.48550/ARXIV.1409.1556.
[19] Zelelew H.M., Almuntashri A., Agaian S., Papagiannakis A.T.: *An improved image processing technique for asphalt concrete X-ray CT images*, Road Materials and Pavement Design, t. 14, nr 2, pp. 341-359, cze. 2013, doi: 10.1080/14680629.2013.794370.
[20] Report TECHMATSTRATEG I, *The innovative technology used the binding agent optimization that provides the long service life of the recycled base course*, National Centre for Research and Development (NCBR), TECHMATSTRATEG1/349326/9/NCBR/2017, 2018.
[21] Selvaraju R.R., Cogswell M., Das A., Vedantam R., Parikh D., Batra D.: *Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization*, 2016, doi: 10.48550/ARXIV.1610.02391.