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The Use of Transfer Learning with Very Deep Convolutional Neural Network in Quality Management

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Grzegorz Kłosowski[1], Monika Kulisz[2], Jerzy Lipski[3], Michał Maj[4,5], Ryszard Białek[6]

Abstarct:

Purpose: *The aim of the article is to develop an algorithm for classifying cracks in the analyzed images using modern methods of deep machine learning and transfer learning based on pretrained convolutional neural network - Inception-ResNet-v2.*
Design/Methodology/Approach: *Transfer learning based on the pretrained convolutional neural network was used to categorize the images. The fully conected layer of the Inception-ResNet-v2 network has been modified. The last layer was trained using a two-class (binary) linear SVM (Support Vector Machine). In total, 20,000 training cases (images) were used to train the fully connected layer within transfer learning process. The research analyzed the possibility of using the deep neural networks for quick and fully automatic identification of cracks / defects on the surface of analyzed parts.*
Findings: *The results indicate that pretrained convolutional neural network using SVM to train a fully connected layer is a very effective solution for visual crack / fault detection. In the analyzed model, a positive classification was obtained at the level of 99.89%.*
Practical Implications: *The model presented in the article can be used in quality control carried out by process monitoring. An effective model for identifying defective parts can be used in both logistics and production processes.*
Originality/Value: *A novelty is the use of a freely available, deep neural network trained to classify 1000 categories of various images for binary categorization of faults (cracks). The algorithm was adjusted by replacing the primary, 1000-output fully connected layer in the Inception-ResNet-v2 network with a binary layer (2 categories). The fully connected layer has been trained using the classification version of the popular SVM learner, but thanks to the combination of this layer with the sophisticated fearure extraction ability of the pre-trained Inception-ResNet-v2 deep network, the resulting predictive model enables the classification of defects with a very high level of accuracy.*

Keywords: *Machine learning, quality management, deep learning, transfer learning, image classification.*

JEL codes: *C45, L15, M11.*
Paper type: *Research article.*

[1]*Corresponding Author, Management Faculty, Lublin University of Technology, Lublin, Poland, g.klosowski@pollub.pl*
[2]*Management Faculty, Lublin University of Technology, Lublin, Poland, m.kulisz@pollub.pl*
[3]*Management Faculty, Lublin University of Technology, Lublin, Poland, j.lipski@pollub.pl*
[4]*University of Economics and Innovation in Lublin, Lublin, Poland, michal.maj@netrix.com.pl*
[5]*Research & Development Centre Netrix S.A, Poland, michal.maj@netrix.com.pl*
[6]*University of Economics and Innovation in Lublin, Lublin, Poland, ryszard.bialek@wsei.lublin.pl*

1. Introduction

Quality management in manufacturing companies is a necessary process to ensure the stability and quality of manufactured products. This is due to the fact that the production process is exposed to non-conformities, which can be detected using appropriate quality management methods and tools (Vasendina *et al.*, 2016). The above tools allow you to control the production process at every stage of production.

The concept of quality can be defined as a set of features of products or services that affect the level of customer satisfaction. Therefore, companies constantly undertake improvement activities in order to meet the requirements set by customers. In order to obtain the appropriate quality, the manufacturing process should be carried out in such a way as to minimize the risk associated with the creation of a product that does not conform to the assumptions (Cheng and Li, 2020). Therefore, control activities play an important role, especially at individual stages of the manufacturing process.

Control and diagnostics of the production process can be conducted as part of self-control carried out by employees directly in production, or performed by the control department. Observations of the production process enable a quick reaction to the noticed differences between the state of implementation of tasks and the assumed plan. The occurring non-conformities, deviations and errors cause that changes are introduced in the implemented activities in order to minimize the effects of non-conformities and improve the efficiency of the process. Control activities are to ensure the appropriate quality of manufactured products, repeatability of received products or services, stability of processes, and thus increase the satisfaction and trust of the company's customers, which is a guarantee of their loyalty. These activities also allow for the detection of non-conforming products and their removal or repair.

The control process consists of three successive stages: measuring the actual performance, comparing the result with the assumed standard, and then, in the event of non-compliance - taking corrective actions to eliminate the deviations. Measurement can be performed by personal observation, measurement systems, statistics and analysis. Various types of devices and sensors are used for the construction of control systems, depending on the type of production, measured quantities, required inspection times, etc.

To assess the quality and correctness of the production process, both at the production stage and in the operational control phase, preference is given to non-invasive diagnostic methods - the so-called non-destructive testing. Such methods include, among others tomography (electric, ultrasound, magnetic) (Rymarczyk and Kłosowski, 2019; Rymarczyk *et al.*, 2019; Rymarczyk, Kozłowski, Kłosowski, and Niderla, 2019; Kłosowski *et al.*, 2020), electromagnetic testing or eddy current method (Li *et al.*, 2021), visual research method (Deng *et al.*, 2018), penetration method (Kryukov *et al.*, 2016) or magnetic method (Tönshoff, Karpuschewski, and Regent, 1999).

The main directions of the use of the eddy current method are the detection of material defects - defectoscopy, testing of material properties - structroscopy and the determination of dimensions (mainly thickness measurements). This method allows the testing of various materials, provided that they are conductors of electric current (Kondej and Szczepański, 2017). The penetration method uses the phenomenon of capillarity - penetration of the liquid pointing deeper into the defects of the tested surface (cracks, pores). The penetration method is used in ferromagnetic and non-ferromagnetic materials and for testing non-metallic materials (e.g. ceramics) (Kryukov *et al.*, 2016). The megnetic method uses the effect of magnetic flux forces on ferromagnetic particles applied to the surface of the tested object and can only be applied to this type of material (Tönshoff, Karpuschewski, and Regent, 1999).

The visual examination method is the method most often used as a preliminary examination in combination with another non-destructive method, which consists in the direct detection and assessment of object discontinuities through direct use of the eye, sometimes assisted by simple optics (Korzeniewska *et al.*, 2020). The vision system, like eyesight, is used to obtain information about the environment and identify specific features, e.g. such as: shape, color, dimensions, surface condition. It allows for data analysis and precise tracking of the production process, and in the case of registration of errors, the implementation of corrective actions. This method most often detects large surface discontinuities (concavities, cracks) and shape defects of the tested object (cavities, porosity, angular deformations, voids) (Deng *et al.*, 2018).

We consider the visual method to be the basic research method in terms of quality control in production processes. It is a visual assessment, it is the employee who uses the sense of sight to control the course and quality of production. It consists in verifying with the naked eye or with the use of optical instruments whether there are errors or non-conformities on the surface of the tested object, and then measuring their appropriate dimensions. This is often associated with the need to have specialized equipment. In order to carry out the checks properly, it is important to have adequate qualifications of employees, their good eyesight, appropriate light intensity and training to distinguish emerging non-conformities. Taking into account the conditions affecting the employee, which may adversely affect the quality control activities performed by him, the following should be distinguished: noise causing inattention of the employee and lowering his productivity, fatigue, monotony of work, time pressure, too many duties.

Human abilities related to quality assessment in production processes are much smaller than the capabilities of a computer with appropriate software based on specialized control algorithms. This is mainly due to the efficiency, duration of the assessment, its repeatability and accuracy in operation. The computer system can also process data from a larger area of the analyzed space, perform multithreaded analysis (simultaneous analysis of various physical quantities is possible), and is also characterized by low unreliability and high stability of the stored pattern.

Various types of vision sensors are most often used in control systems. Examples of types of vision sensors are: color sensors - emitting light and comparing the chromatic coordinates of the reflected radiation with previously adopted patterns, luminescence sensors - emitting ultraviolet light to find markers invisible to the eye, gray scale sensors - based on a reflected beam of infrared light, contrast sensors - analyzing the reflectance of radiation (Vu *et al*., 2012; Wei, *et al*., 2016). Cameras are slightly more advanced devices for collecting visual data from the environment, which allow for the simultaneous acquisition of data from many points, moreover, it is possible to examine several features of a given slice at the same time, and the image analysis can be multi-threaded, and consequently comprehensive.

Due to the increasing technological progress and the development of new industrial paradigms such as production 2.0, industry 4.0, Smart Factory, Internet of Things, machine learning (ML) methods are increasingly used in the quality management of production processes. One of the main problems in production lines is the detection of faults, defects, irregularities and non-conformities of final products, as well as real-time process monitoring (Kozłowski *et al.*, 2019). The solution to these problems may be the classification of images from the vision system using machine learning methods.

These techniques allow the use of computer tools to perform complex tasks such as: classification, categorization, prediction, diagnosis, planning or pattern recognition based on historical data. The results of the analyzes are influenced by the quality and number of learning data, as well as the use of appropriate algorithms. ML techniques are used in many areas depending on the type of problem to be solved. There are, among others, the following types of tasks: regression (for prediction of one variable - numerical value - based on the known values of input variables), classification (allowing to find a mapping of unknown data in a set of predefined classes using the created model called a classifier), and clustering (dividing data points into appropriate groups). In the first two cases, we deal with supervised learning, and clustering is carried out with the use of unsupervised learning (Kang, Catal, and Tekinerdogan, 2020).

Most often, in the case of detecting defects related to categorizing images, classification solutions using deep learning algorithms are used. CNN (convolutional neural network) and LSTM (long short-term memory) (Kang, Catal, and Tekinerdogan, 2020). CNN is a powerful tool in image recognition, which has been repeatedly demonstrated in many fields (Krizhevsky, Sutskever, and Hinton, 2012; Karpathy *et al.*, 2014; He *et al.*, 2016; Atabay, 2016a). As a type of deep learning approach, CNN has revolutionized the field of pattern recognition thanks to its efficiency and impressive performance in a wide variety of classification tasks. CNN can be used in various areas of life, e.g., in agriculture, for the segmentation and classification of images containing sought objects, such as animals, fruits or leaves (Atabay, 2016a; 2016b; Cecotti *et al.*, 2020). The classification of contours / sketches was also dealt with in their works by other researchers, e.g., Yu *et al.* (2016) whether

Zhang *et al.* (2016) who analyzed images in their research contains 250 categories with 80 sketches per category (human sketch dataset), the categories were related to life, among others everyday. CNN was also used in the detection of defects in historic buildings, which was done by Mansuri and Patel (2021). Australian researchers Vo *et al.* (2020) point to the use of CNN for image-based identification of products in the supply chain using the example of the American Lobster. As indicated by the analysis carried out above, CNN can be effectively used for pattern recognition.

In terms of using CNN in production processes and fault detection, you can find in the literature, among others such solutions as, detection of defects in the texture of the fabric (Arora and Hanmandlu, 2021), recognition of the operator's face, classification of Human Machine Interface (HMI) consoles, detection of errors on the LCD display and classification of the state of pressure buttons (*Variz et al.*, 2019) or classification of fruit quality into three classes (Yogesh *et al.*, 2020).

The analysis carried out above shows that CNN can be effectively used to recognize patterns in images from cameras. The aim of the article is to develop an algorithm that uses pre-trained neural convolution to detect material defects. The study used transfer learning based on the pretrained very deep convolutional neural network - Inception-ResNet-v2 (Ioffe and Szegedy, 2015; Szegedy *et al.*, 2017). The task of the developed algorithm was to identify the cracks recorded in the images as a result of using this model during control operations during manufacturing processes.

2. Research Methodology

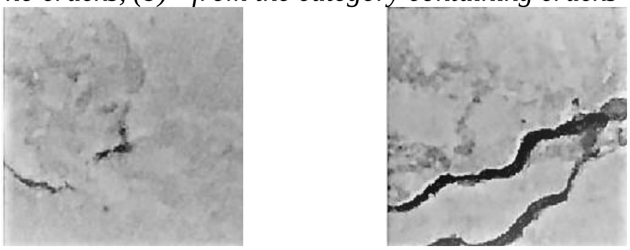
The transfer learning method based on the pretrained convolutional neural network - Inception-ResNet-v2 was used to detect faults and classify cracks in the analyzed objects. Transfer learning allows you to significantly shorten the network learning process by using an already existing model that has been previously trained to solve a specific problem (e.g., image classification). Adapting the network through transfer learning is usually faster and easier than teaching the network from scratch, as you can only change the last layer of the pre-trained network model and use a new, smaller dataset to train the new output layer (Weiss, Khoshgoftaar, and Wang, 2016; Quiñonez *et al.*, 2019).

The pretrained Inception-ResNet-v2 convolutional neural network was used to solve the analyzed problem, which was developed by Google on the basis of the Inception Net model and is taught on over a million images from the ImageNet database. This network was selected due to the fact that it is dedicated to classifying images and has the ability to classify images into 1000 object categories. This network consists of 825 layers and an image input size of 299-by-299. In pretrained Inception-ResNet-v2 network modified to fully conected layer by adjusting exits. Instead of the original number of thousand classes, a binary approach was used, defining two classifiers: an image containing cracks (defective) and an image without visible cracks (correct).

In the studies described below, images from the dataset are categorized using a two-class linear SVM (Support Vector Machine) trained with CNN traits extracted from the images. This approach to classifying image categories follows the standard practice of training a common classifier using features extracted from images. The difference is that instead of using image features such as HOG or SURF, the image features are extracted using pretrained CNN.

The research used a publicly available set of images, which was used to finally train the SVM classifier. The collection was made available as part of the publication entitled Concrete Crack Images for Classification (Özgenel, 2019). The collection includes images with and without cracks. Sample images used to train the neural model are shown in Figure 1.

***Figure 1**. Examples of images included in the data set: (a) - from the category containing no cracks, (b) - from the category containing cracks*

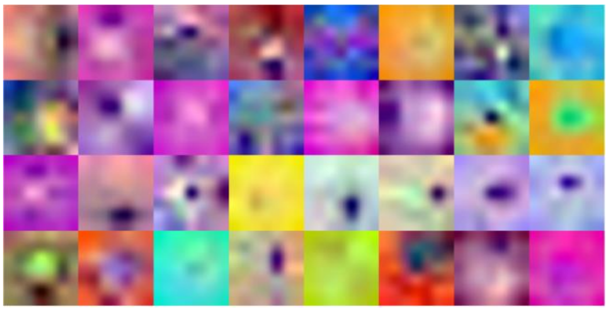


(a) **(b)**

***Source:** Own creation on the basis of* Özgenel, 2019.

Figure 2 shows a visualization of the 32 features identified by the first convolutional layer ("conv2d_2"). Thanks to the visualization, you can see how the first layer of the network learned the filters to capture Blob and Edge features. For image processing, a blob is defined as an area of combined pixels.

***Figure 2**. Visualization of 32 features identified by the first convolutional layer („conv2d_2”)*



***Source:** Own creation.*

Blob analysis is the identification of a region in an image and distinguish between pixels based on their values and put them into one of two categories, foreground or background. A blob is an area of contacting pixels, and analytical tools treat touching foreground pixels as part of the same Blob. These "primitive" features are then processed by deeper network layers that combine the early features to create higher-level image features. These higher-level features are better suited for recognition tasks because they combine all primitive features into a richer image representation.

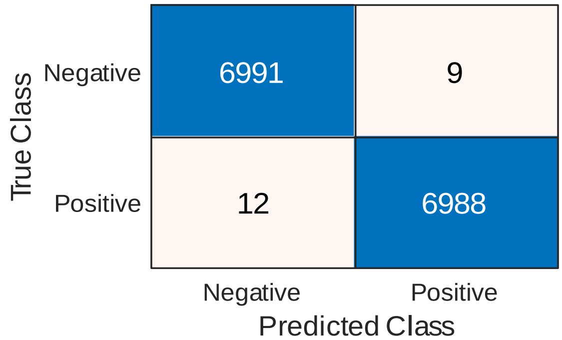
We can easily extract features from one of the deeper layers using the activation method. Choosing deep layers to choose from is a design choice, but usually a good start is to start with a layer just before the classification layer. In the network, this layer is called "forecasts". Let's distinguish the training features with this layer. The activation function automatically uses the GPU for processing if available, otherwise the CPU (central processing unit) is used. In this code, "MiniBatchSize" is set to 32 to ensure that CNN and image data fit in the GPU memory. You may need to lower "MiniBatchSize" if the GPU runs out of memory. In addition, the activation output is arranged as columns. This helps to speed up subsequent multi-class SVM line training.

3. Results

A total of 20,000 images were tested, 10,000 for each of the two categories. As mentioned before, Inception-ResNet-v2 can only process RGB images with dimensions of 299 by 299. To avoid rewriting all images in this format, an appropriate piece of the algorithm was used to resize and convert the grayscale images to RGB. The analyzed set was divided into training (30%) and validation (70%) data.

The training of a two-class (binary) SVM classifier based on the characteristics obtained from CNN was done by using the Stochastic Gradient Descent quick solver, which is used for training by setting the "learners" parameter to "linear". This helps speed up training when working with CNN's multivariate feature vectors. Then, the effectiveness of the classifier was assessed. The result of this analysis in the form of a confusion matrix of two is presented in Figure 3.

Figure 3. *The confusion matrix of two classes of crack occurrence for the analyzed model*

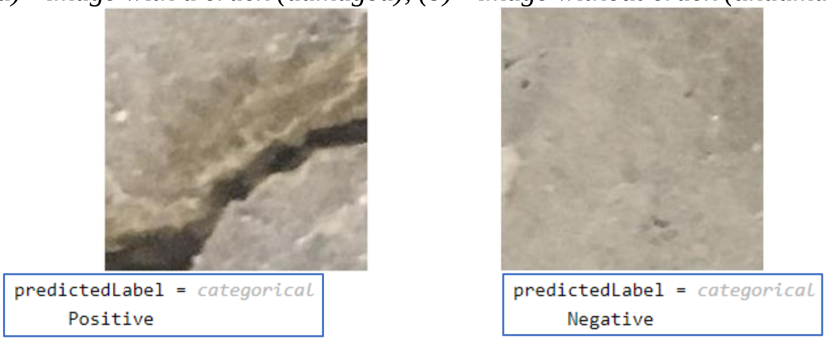


Source: *Own creation.*

To test the quality of the classifier, 7,000 images were used that did not participate in the learning process. The images with cracks were correctly classified in 99.83% and the images without cracks in 99.87%. The average quality of the obtained model for crack detection is 99.83%. The high efficiency of the presented classifier allows to state that it can be successfully used to detect cracks / defects based on the analyzed images.

Figure 4 shows an example of the result of the CNN algorithm using transfer learning from Inception-ResNet-v2 deep network. The category name appears below the classified image. In Figure 4a, the algorithm recognized the damage by assigning the *predictedLabel* variable the *Positive* category. For images with no damage (Figure 4b), the *predictedLabel* variable is assigned the *Negative* category.

Figure 4*. An example of the operation of a trained classifier on a test image: (a) - image with a crack (damaged), (b) - image without crack (undamaged)*



(a) **(b)**

Source: *Own creation.*

4. Conclusions

This study presents the original algorithm that enables the classification of material defects with the use of very deep CNN and transfer learning. A pre-trained convolutional neural network (CNN) was used as a feature extractor (transfer learning) to train a binary image classifier. The widely available convolutional neural network Inception-ResNet-v2 has proved to be a very effective tool for transfer machine learning. The Inception-ResNet-v2 network has been trained with large collections of diverse images. From these, CNN, originally having 1000 output grades, learned to classify rich trait representations for a wide variety of images. These feature representations often outperform manual feature extraction methods such as HOG, LBP, or SURF. A good way to harness the potential of CNN was to use a pre-trained network as a preprocessing tool.

In the research described, images from the dataset were categorized using a two-class linear SVM (Support Vector Machine) trained with CNN features extracted from the images. The layer with the binary SVM classifier acts as a fully connected layer. This approach to classifying image categories follows the standard practice of training a common classifier using features extracted from images. The difference is that instead of using image features such as HOG or SURF, the image features are extracted using pretrained CNN. The research utilized a publicly available set of images, which was used to finally train the SVM classifier.

The use of very deep CNN and SVM transfer learning has brought very positive results. The original trained classifier is effective at the level of 99.98%. Out of 7,000 tested images containing undamaged objects, the CNN classifier incorrectly classified only 13. Out of 7,000 images showing cracks, there were only 3 misclassifications. Such high efficiency enables the use of the new classifier in practical applications. In particular, the models described in this study can be used in the field of production and logistics. They can be successfully used in automated vision quality control systems whose task is to monitor parts, goods or products in order to identify all kinds of defects that can be identified through surface observation.

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