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A comparison of two various artificial intelligence approaches for the corrugated board type classification †

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Abstract: Corrugated board is an environment-friendly, commonly used packing material. Its basic structure consists of two liners and a flute between them. Mechanical properties and strength of corrugated board depend on constituent papers but also on its geometry. Which , however, can be distorted due to various factors related to its manufacture process or use. The greatest distortion occurs in the corrugated layer, which, due to crushing, significantly deteriorates functional properties of cardboard. In this work, two algorithms for automatic classification of corrugated board types based on images of deformed corrugated boards using artificial intelligence methods are presented. A prototype of corrugated board sample image acquisition device was designed and manufactured. It allowed to collect an extensive database of images with corrugated board cross-sections of various types. Based on this database, two approaches for processing and classifying them were developed. The first method is based on identification of geometric parameters of the corrugated board cross-section using a genetic algorithm. After this stage, a simple feedforward neural network was applied to classify the corrugated board type correctly. In the second approach, the use of a convolutional neural network for corrugated board cross-section classification was proposed. The results obtained using both methods were compared, and the influence of various imperfections in the corrugated board cross-section was examined.

Keywords: corrugated board; cross-section image; genetic algorithm; feedforward neural network; convolutional neural network

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1. Introduction

Corrugated board is commonly employed in the packaging of food products, transportation of diverse goods, and several other packaging applications. The primary benefits of this product include its lightweight nature and ease of handling. In addition, the product has the capability to be printed with personalized graphics. Corrugated board possesses the capacity for recycling and biodegradability, rendering it a favorable option from an environmental standpoint for both commercial enterprises and individuals. The material in question is widely utilized in the packaging industry due to its versatility and popularity [1,2]. The composition of this construction includes a rigid sheet and two smooth linerboards, which contribute to its durability and strength while also allowing for flexibility.

The formation of the flute, which is the ridged sheet found in corrugated board, is achieved by passing paper through a sequence of grooving rolls. These rolls are responsible for creating the characteristic ridges and depressions. This is the reason why the corrugated board is referred to by such a designation. The flute is available in a variety of dimensions. The larger flutes provide enhanced structural integrity and improved shock absorption, whereas the smaller flutes offer a more refined printing surface. Examples of various types of corrugated boards analyzed in this study are presented in Figure 1.

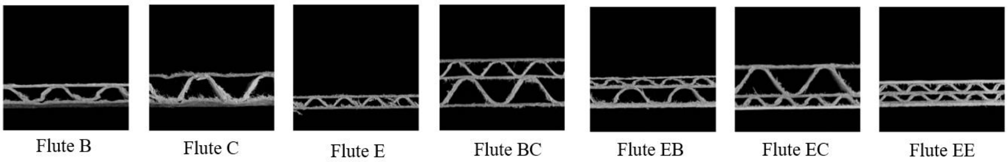


Figure 1. Examples of various corrugated boards types cross-sections analyzed in this work.

In the literature, various geometries or materials classifications were performed based on cross-sectional images. The support vector machine was used by Caputo et al. to classify materials [3]. The authors examined images under various pose and illumination conditions. Woden fabrics classification with the use of the convolutional neural network (CNN) was proposed by Iqbal Hussain et al. [4]. They applied a pretrained network architecture ResNet-50. Wyder and Lipson identified static and dynamic properties of cantilever beams using their raw cross-sectional images and CNNs [5]. Comparison of various deep learning techniques for analyzing geometric features of self-piercing riveting cross-section was performed by Li et al. [6]. They concluded that using Unet and SOLOv2 architectures one can obtain the best results. Analysis of crushed thin-walled carbon fiber-reinforced polymer tubes cross-sections taking into account their geometrical features was performed by Ma et al. [7]. In this work, it is proposed to identify corrugated board type based on their cross-sectional images. In the literature, one can find many papers, in which the corrugated board is analyzed numerically using computational models. The approach presented in this paper is a first step in automatic generation of computational models representing real structures for numerical simulation.

In this paper, two approaches for classification of corrugated board cross-section types are analyzed and compered. The first one approach is based on basic image processing operations, genetic algorithm and feedforward neural network, while the second approach employs the CNN.

2. Materials and methods

3.1. Corrugated board cross-section samples acquisition

A special device was created and manufactured using 3D printing technology to capture the photos of the corrugated board cross-section. More details can be found in [8] (pp. 3-4). The system employed a Sony IMX179 (1/3.2”) image sensor with an 8 MPx resolution and an ArduCam B0197 camera with autofocus. The resolution of the image was 3264 x 2448 pixels.

The obtained image dataset consisted of 646 different samples from different sources and with various imperfections (e.g., crushed fluting, delaminated layers, protruding cellulose fibres, etc.).

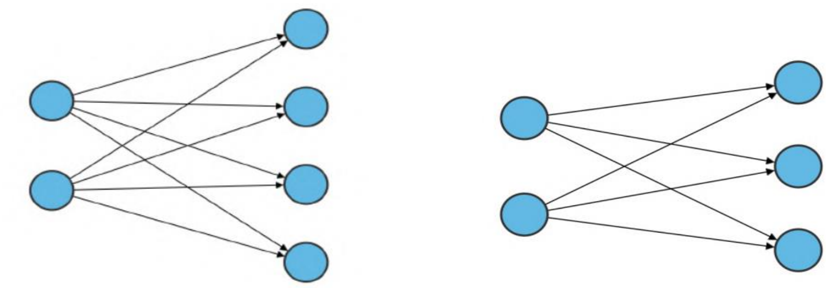
3.2. Approach based on identification of geometric features using genetic algorithm and feedforward neural network

In the first approach, the feedforward neural networks (FFNNs) were used to classify the corrugated board type. In order to achieve this goal, the methodology presented in [8] with application of the genetic algorithm (GA) was employed to calculate the input parameters of FFNNs. The following parameters of the GA were used in this study:

- maximal number of iterations: 500;
- population size: 100;
- mutation probability: 0.15;
- elite group ratio: 0.01;
- crossover probability: 0.2;

- parents portion: 0.2;
- crossover type: uniform.

The details of the algorithm applied for obtaining the parameters can be found in [8]. The structure of applied FFNNs and input parameters differ for single- (3 ply) and double- (5 ply) walled corrugated boards. The number of layers of the corrugated board is determined applying the method presented in [8]. After that, the appropriate FFNN structure can be used. For 3ply corrugated boards the input parameters were: fluting height and period, while for 5ply flutings periods were taken as the input parameters. The FFNN in both cases consists of two inputs and single layer of neurons. The softmax function was applied as a activation function. In the training process, the ADAM optimization method was applied.

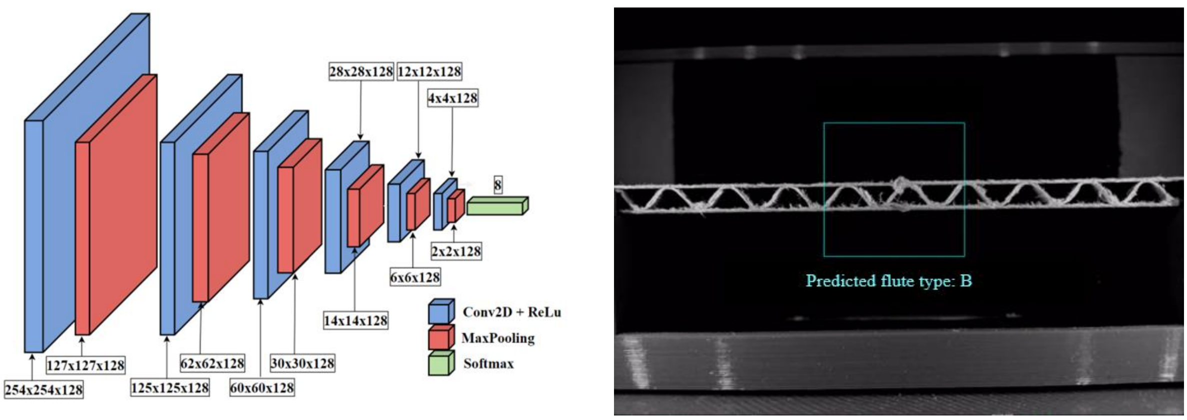


(**a**) (**b**)

Figure 2. Structures of the feedforward artificial neural networks for classification of corrugated board type for: (**a**) double- (5 ply) or (**b**) single- (3 ply) walled corrugated boards.

3.3. Approach based on convolutional neural network classification

In the second approach, the CNN was employed to classify the corrugated boards. The gray-scale images of size 255x255 were the inputs to the applied CNN, which consisted of six convolution layers, each one followed by max pooling layer. In the end of the CNN structure, the softmax layer was applied. The complete CNN structure is shown in Figure 3a. The trained CNN model can be used in a real-time vision system, example of which is presented in Figure 3b. The ADAM optimization method was applied for the training process of the CNN.

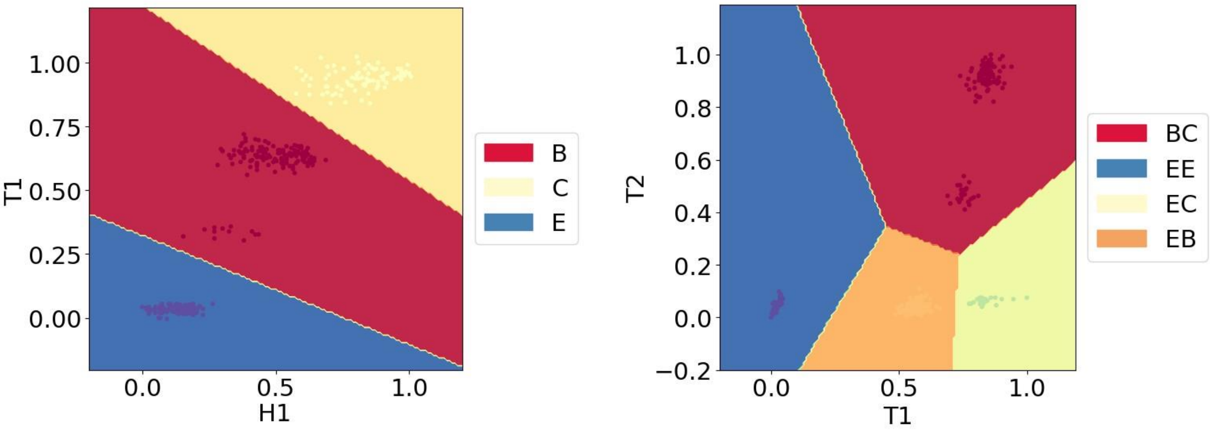


(**a**) (**b**)

Figure 3. (**a**) Structure of convolutional neural network applied in this work; (**b**) real-time vision system.

3. Results

In the first approach, using the GA, in both cases two parameters of the FFNN were employed. Therefore, the decision boundaries can be presented in a graphical form shown in Figure 4.



(**a**) (**b**)

Figure 4. Decision boundaries for trained feedforward neural networks designed for: (**a**) single- (3 ply) or (**b**) double- (5 ply) walled corrugated board.

The obtained classification accuracy were equaled:

- 98.3% for the first approach using the GA and FFNN;
- 99.4% for the second approach using the CNN.

Table 1 presents the inference times for various flute types. One can notice that the first approach results in much higher inference times. Furthermore, in case of double-walled corrugated boards, the inference times is doubled due two processing and calculations for two flutes.

Table 1. Inference times for various flute type for both approaches.

Flute type	Approach I – GA + FFNN [s]	Approach II – CNN [s]
B	14.21	0.110
C	12.82	0.106
E	13.52	0.104
BC	24.82	0.113
EB	25.23	0.122
EC	22.92	0.127
EE	23.34	0.116

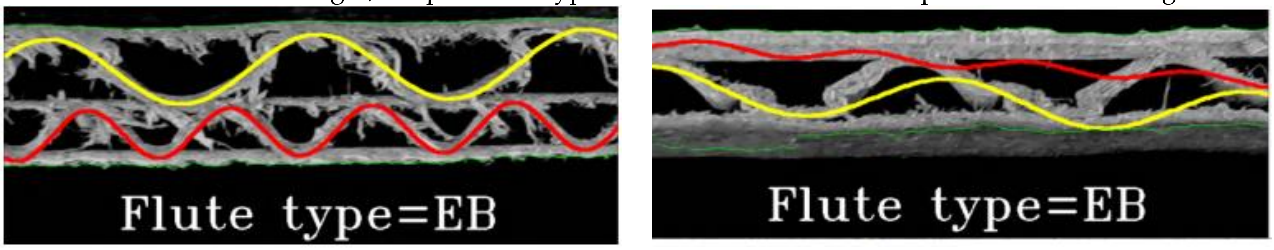
4. Discussion

As it was mentioned in the previous section, the classification accuracy for the first approach was equal to 98.3%. Only 13 images in this case were wrongly identified. 9 of them depicted single-walled (3 ply) corrugated boards. Furthermore, all of them were crushed or stochastically deformed.

The classification accuracy for the CNN was equal to 99.4%. In this case, 10 images were incorrectly classified. 9 of them present single-walled (3 ply) corrugated boards. The same number of images among them were stochastically deformed or crushed.

Analyzing the results obtained for the first approach, one can notice that protruding cellulose fibers and jagged cutting edges do not significantly affect the flute shape approximation (Figure 5a) and one can obtain the proper classification results. However, the error of classification appear in many cases when the liners are bent. In such a case, the propose algorithm can detect two flutes, while only one of them exists in the real structure, see Figure 5b. Therefore, the single-walled corrugated boards can be recognize as double-walled in such a case.

In the second approach, similarly the cellulose fibers and jagged cutting edges do not significantly affect the classification results. The classification errors are made often if the level of crush in the corrugated board structure is higher. Among the incorrectly classified images, the predicted type was rather lower than this presented in the image.



(**a**) (**b**)

Figure 5. Examples of corrugated board samples with: (**a**) jagged edges and cellulose fibres (**b**) bent liners.

5. Conclusions

The results obtained using both approaches, compared in this paper, were very accurate. However, the higher accuracy and shorter inference times were obtained for the second approach with the use of CNN. The obtained results can be still improved in the future works.

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