engineering proceedings

Proceeding Paper

A Comparison of Two Artificial Intelligence Approaches for Corrugated Board Type Classification †

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† Presented at the 4th International Electronic Conference on Applied Sciences, 27 October–10 November 2023; Available online: https://asec2023.sciforum.net/.

Abstract: Corrugated board is an environmentally friendly, commonly used packing material. Its basic structure consists of two liners and a flute between them. The mechanical properties and strength of the corrugated board depend not only on the constituent papers but also its geometry, which can be distorted, however, due to various factors related to its manufacturing process or use. The greatest distortion occurs in the corrugated layer, which, due to crushing, significantly deteriorates the functional properties of cardboard. In this work, two algorithms for the automatic classification of corrugated board types based on images of deformed corrugated boards using artificial intelligence methods are presented. A prototype of a corrugated board sample image acquisition device was designed and manufactured. It allowed for the collection of 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 the identification of the 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

Citation: Rogalka, M.; Grabski, J.K.; Garbowski, T. A Comparison of Two Artificial Intelligence Approaches for Corrugated Board Type Classification. *Eng. Proc.* **2023**, *56*, 272. https://doi.org/10.3390/ASEC2023-15925

Academic Editor: Nunzio Cennamo

Published: 8 November 2023

1. Introduction

Corrugated board is commonly employed in the packaging of food products, the 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. Larger flutes provide enhanced structural integrity and improved shock absorption, whereas smaller flutes offer a more refined printing surface. Examples of the various types of corrugated boards analyzed in this study are presented in Figure 1.

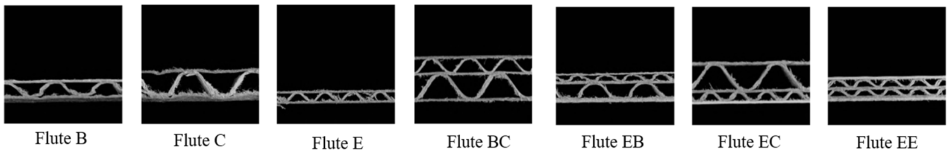


Figure 1. Examples of the various corrugated board type cross-sections analyzed in this work.

In the literature, various geometries or material classifications have been performed based on cross-sectional images. A support vector machine was used by Caputo et al. to classify materials [3]. The authors examined images under various poses and illumination conditions. Woven fabric classification with the use of a convolutional neural network (CNN) was proposed by Iqbal Hussain et al. [4]. They applied a pre-trained network architecture, ResNet-50. Wyder and Lipson identified the static and dynamic properties of cantilever beams using raw cross-sectional images and CNNs [5]. A comparison of various deep learning techniques for analyzing the geometric features of self-piercing riveting cross-sections was performed by Li et al. [6]. They concluded that by using U-Net and SOLOv2 architectures, one can obtain the best results. Analysis of crushed thin-walled carbon fiber-reinforced polymer tube cross-sections, taking into account their geometrical features, was performed by Ma et al. [7]. In this work, it was proposed to identify corrugated board types 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 the automatic generation of computational models representing real structures for numerical simulation.

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

2. Materials and Methods

2.1. Corrugated Board Cross-Section Sample 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 (Atsugi, Japan) with an 8 MPx resolution and an ArduCam B0197 camera with autofocus. The resolution of the images was 3264 × 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 fibers, etc.).

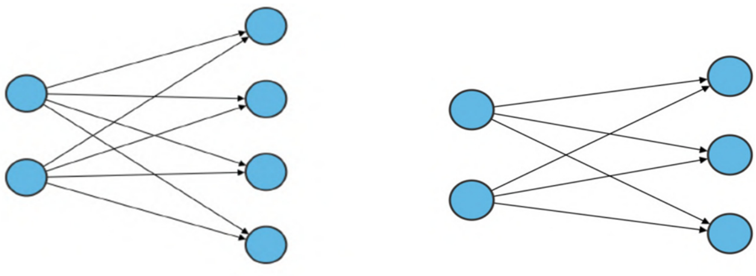
2.2. Approach Based on the Identification of Geometric Features Using a Genetic Algorithm and Feedforward Neural Networks

In the first approach, FFNNs were used to classify the corrugated board type. In order to achieve this goal, the methodology presented in [8] with the application of a genetic algorithm (GA) was employed to calculate the input parameters of the FFNNs. The following parameters for 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 to obtain the parameters can be found in [8]. The structure of the applied FFNNs and the input parameters differ for single (3-ply)- (see Figure 2a) and double (5-ply)-walled corrugated boards (see Figure 2b). The number of layers in the corrugated board was determined by applying the method presented in [8]. After that, the appropriate FFNN structure could be used. For 3-ply corrugated boards, the input parameters were the fluting height and period, while for the 5-ply corrugated boards, the fluting periods were taken as the input parameters. The FFNN in both cases consists of two inputs and a single layer of neurons. The SoftMax function was applied as an activation function. In the training process, the ADAM optimization method was applied.

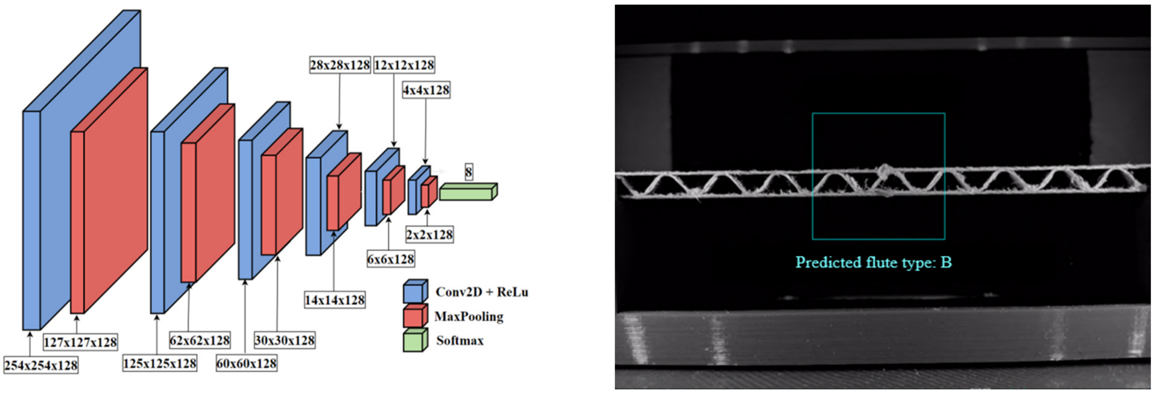


(**a**) (**b**)

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

2.3. Approach Based on Convolutional Neural Network Classification

In the second approach, a CNN was employed to classify the corrugated boards. The gray-scale images of size 255 × 255 were the inputs to the applied CNN, which consisted of six convolution layers, each one followed by a max pooling layer. At 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, an 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**) The structure of the convolutional neural network applied in this work and (**b**) the 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, as shown in Figure 4.

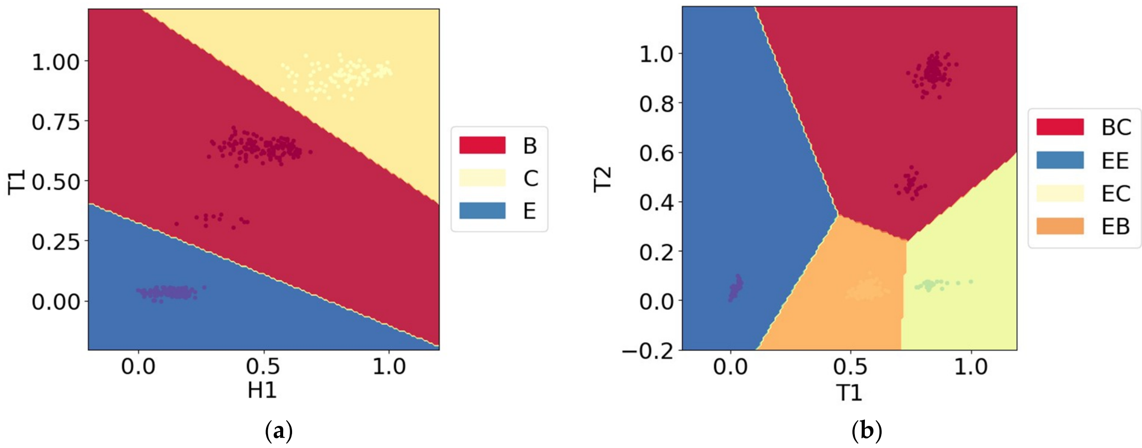


Figure 4. Decision boundaries for trained feedforward neural networks designed for (**a**) single (3 ply)- or (**b**) double (5 ply)-walled corrugated board.

The obtained classification accuracy 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 the case of double-walled corrugated boards, the inference times are doubled due to there being two processing and calculations stages for two flutes.

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

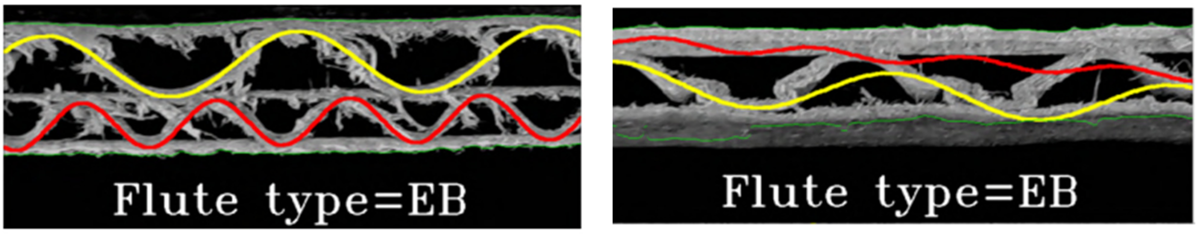
Flute Type	Approach I—GA + FFNN [s]	Approach II—CNN [s]
B	14.21	0.110
C	12.82	0.106
E	13.52	0.104
BC	24.82	0.113
EB	25.23	0.122
EC	22.92	0.127
EE	23.34	0.116

4. Discussion

As 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. In total, nine of them depicted single-walled (3-ply) corrugated boards. Furthermore, all of them were crushed or stochastically deformed.

The classification accuracy of the CNN was equal to 99.4%. In this case, 10 images were incorrectly classified. A total of nine of them presented 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 appears in many cases when the liners are bent. In such a case, the proposed 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 recognized as double-walled in such a case.



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

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

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

5. Conclusions

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

Author Contributions: Conceptualization, T.G. and M.R.; methodology, M.R. and J.K.G.; software, M.R.; validation, M.R., J.K.G. and T.G.; formal analysis, M.R.; investigation, M.R. and J.K.G.; resources, M.R. and T.G.; data curation, M.R.; writing—original draft preparation, M.R., J.K.G. and T.G.; writing—review and editing, J.K.G. and T.G.; visualization, M.R.; supervision, J.K.G.; project administration, J.K.G. and T.G.; funding acquisition, J.K.G. and T.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are available upon request.

Acknowledgments: The authors would like to thank Kacper Andrzejak from the Werner Kenkel company and Monika Niziałek-Łukawska and Małgorzata Kuca from the Schumacher Packaging company for providing the research materials. We would also like to thank the Femat company for providing financial support for the conducted research and for the possibility of using their laboratory equipment as well as their professional software.

Conflicts of Interest: The authors declare no conflicts of interest.

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