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# REMANUFACTURING PROCESS IMPROVEMENT BY IMAGE RECOGNITION METHODS. APPLICATION OF THE MECHANICAL PART

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The paper describes the possibility of using, building, and implementing an image recognition system in a company performing remanufacturing processes. It is based on a thesis prepared with the help of Wabco Reman Solutions. The tests were conducted using one of the parts remanufactured by the company – a manifold. The research focuses on different variants of the obtained image recognition models in order to identify differences that may affect their effectiveness and possible application in real work conditions. The environment used to build the models is Jupyter Notebook, and convolutional neural networks were implemented.

## 1. INTRODUCTION

In the era of continuous economic development, the ability to automate operations in production systems is an important issue. Remanufacturing processes, which are becoming more and more popular, rely on their reuse, applying technological operations that regenerate a given element. These processes are very desirable nowadays, as they are based on ecological thinking and reduce environmental pollution. This is achieved not only by reducing waste resulting from the need to place an item that has completed its life cycle in a landfill; the remanufacturing process itself usually requires significantly less energy expenditure compared to the original production process. Unfortunately, the remanufacturing processes are not standard, but depend on the degree of wear of a given element. Some elements cannot be remanufactured because the damage is too extensive and their restoration is not profitable in any respect. An identification of defects on elements that constitute raw material for the process, often called "core", is thus a very important element of the remanufacturing process. At most companies associated with this in-

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dustry, defect identification is done manually as they do not have the right tools for autonomous work. However, technological development has allowed the industry to utilize a tool for autonomous image recognition using convolutional neural networks. This type of identification can be accomplished by teaching a given network to use input data that present a relevant sample of photographs of defects of a given element and a sample of photographs of an element that is acceptable for the remanufacturing process.

## 2. REMANUFACTURING PROCESS

The development of production in the recent years leads to noticeable climate change, manifested by increased pollution. In order to counteract further climate change, new solutions relating directly to production-focused activities are proposed. One of these is remanufacturing, which makes companies applying this process become "green" in the eyes of society. This is due to the fact that a product subject to the remanufacturing process has an extended life cycle, which results in less pollution being produced, and the process itself consumes less energy compared to the original production [1].

### 2.1. PROCESS DESCRIPTION AND BENEFITS

As a general rule, any product can be remanufactured. However, not all of them should be subject to this process, as it would not be economically justified. One of the most important requirements is that the cost of rejected material and product consumption should be as low as possible, and the component re-processing cost should not exceed the cost of producing a new item. In addition, the product should meet several other properties, such as:

- durability,
- functional failure,
- standardization of replaceable parts,
- high added value,
- low purchase cost,
- stable technology,
- customer awareness of the product's origin [2].

Remanufacturing is an industrial process in which used products are regenerated in such a way they meet as many conditions of quality as possible, compared to the original product. In fact, remanufactured products usually have the same quality as the initial product, with one difference being warranty reduction from 100% to 70% compared to the original. The remanufacturing process can be divided into four different stages: control/classification, disassembly of components, reprocessing of parts, reassembly/testing. A diagram of this division is shown in the Figure 1 [2].

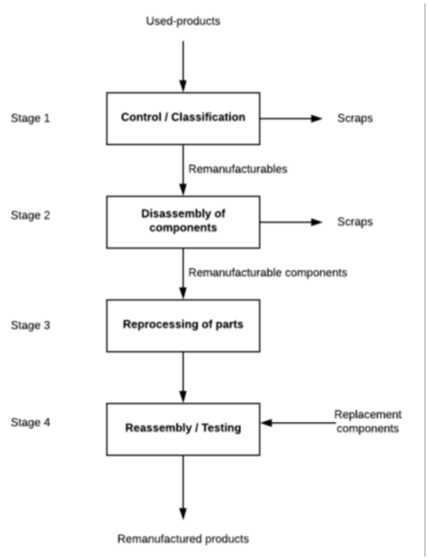


Fig. 1. Stages of remanufacturing process [2]

In the age of universal responsibility for the planet and education focused on environmental problems such as global warming, it is common knowledge that environmental benefits are of great importance. However, the positive impact of remanufacturing involves many other factors that relate to running a business. These benefits are as follows:

- remanufacturing process reduces the amount of materials used to manufacture a given product, and technological processes usually consume less energy, which translates into financial and ecological savings,
- the technological process is less monotonous compared to the original one, as operators face many different cases; this increases creativity and dedication of employees,
- customer buys a product of the same quality, but at a much lower price, reaching up to 60% of the basic price of the product,
- reducing penalties for enterprises related to the need to recycle a certain amount of their products due to the fact that the remanufacturing process extends the product life cycle,
- products subject to remanufacturing are often implemented faster due to the lack of need to perform long process machines,
- possibility to use knowledge regarding dismantling and reassembling shared by former operators of other manufacturing companies [3].

### 2.2. MAIN ISSUES

Solving problems and facing challenges are the main issues every engineer at a production company must take into account. Their complexity and frequency of occurrence is influenced, among others, by the stability and automation of the entire process and all subprocesses. It is well known that the main factor determining the remanufacturing process is the state of the core, which comes in the form of raw material. Unfortunately, after the end of their life cycle, products have different properties and defects. Therefore, the whole process is less stable than manufacturing process, and thus more attention-demanding [3].

Although process-related difficulties are certainly a major challenge for remanufacturing companies, they are not the only factors affecting their work. Several types of issues, which are the most important factors to control in order to manage a remanufacturing company, are listed below:

- **designing a product for remanufacturing** – when designing a product, a large number of manufacturing companies do not take into account that it might undergo a remanufacturing process in the future. In consequence, remanufacturing companies struggle with the proper performance of basic operations such as disassembly or reassembly,
- **the process of obtaining returns** – unlike original production process, where raw material is easily accessible on the market, remanufacturing relies on the uncertainty associated with the supply of raw material – the cores. This complexity is manifested even more as the cores do not always pass the criteria of initial assessment, and therefore some of them are not suitable as raw material,
- **process issue** – the most important activities that also take the most time during the remanufacturing process are disassembly, cleaning, recovery of parts, and reassembly. Disassembly process should not be the reverse of assembly. The slowness and cost of this process are affected by factors such as product complexity, types of fastening used, presence of corrosion, product homogeneity, and even product size or the order of disassembly,
- **employees' level of expertise** – remanufacturing is a time-consuming process. This is due to a dynamic and diverse work environment. Therefore, employees working in this type of production should have experience enabling them to make informed decisions,
- **inventory management** – not all parts and components are reused during the remanufacturing process, as it would be economically unjustified (as described in the previous section). For this reason, companies must stock up on spare parts, the number of which will depend on the unknown number of cores,
- **marketing of remanufactured product** – the problem is related to customers' lack of awareness of the quality of the product, and even of what the remanufacturing process is [4].

## 3. ACCEPTANCE CRITERIA OF MANIFOLDS

Each company has its own acceptance criteria for the initial material and the final product. In the case where a product after completing its life cycle is treated as material for the process, it is necessary to apply criteria that will reflect it to all the possible defects. This task is difficult due to the existence of many possible defects that can lead to rejecting the product as scrap. Wabco Reman Solution has decided to create not fully standardized acceptance criteria that will make a relative assessment of a given part possible. This is resolved in such a way as to show the worst defect acceptable for the further process and to describe it properly so that it is understandable to a person performing the assessment. All defects which pose a severe threat to the proper functioning of the parts on the basis of the description and the photograph are rejected and treated as scrap metal, and are not subject to remanufacturing process. Based on this information, it can be seen that this assessment is performed in a subjective way, but necessary to ensure continuity and process stability. Figure 2 shows an example of the acceptance criteria for aluminum work surface [5].

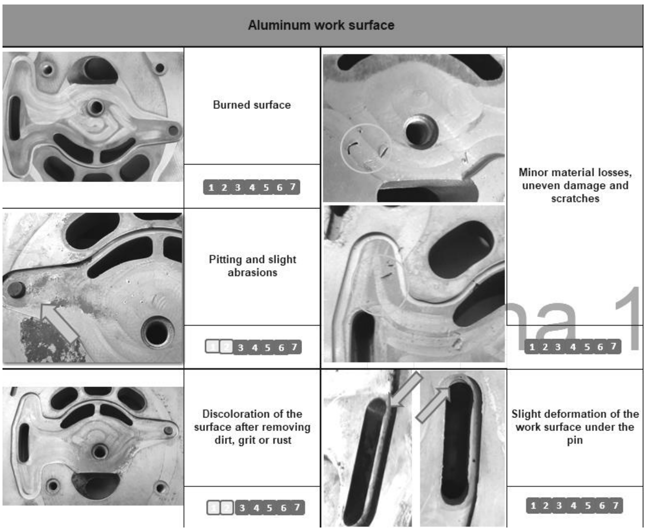


Fig. 2. Acceptance criteria for aluminum work surface [5]

Manifolds have several acceptance criteria, which differ in terms of complexity and assessment difficulties. In this paper, two criteria are taken into account and evaluated in this part. An important factor influencing this decision was achieving a comparison of how effective a given neural network can be in assessing a given defect, so that it is able to formulate conclusions defining the possibilities of using a given network or data on the aspects that should be improved.

Eventually, it was decided to choose two defects located on two different surfaces selected for analysis. These surfaces are sealing surface and mounting surface, both presented in the Figure 3. The main factor influencing this choice was whether working conditions at the workstation were achievable. Some other areas would require equipment that was not supplied, so efforts were made to fully use the available equipment.

Another important factor is that in order to be able to completely use its potential, a neural network needs a very large amount of input data, which it uses to learn by creating a matching weight vector map. In the initial stages of the project, not enough parts were delivered on the basis of which the desired effect could be achieved. Therefore, it was initially decided to select defects whose in-depth assessment can be carried out, even on the basis of a minor amount of input data. Defects of this type are characterized by more shape regularity, and their probability of occurrence in specific areas is higher.

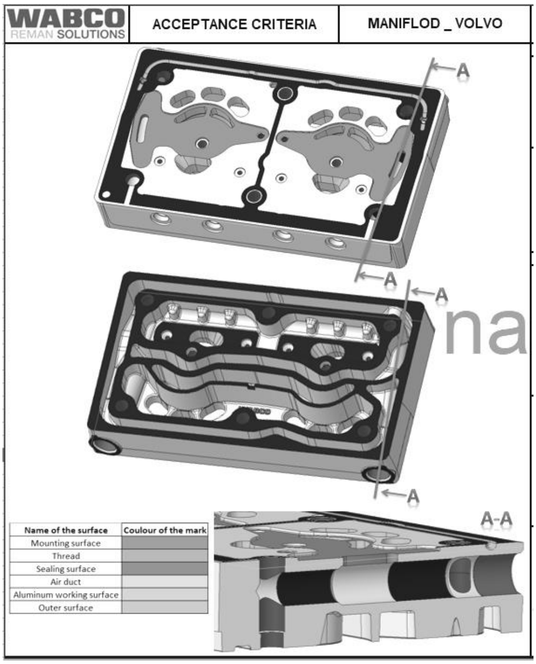


Fig. 3. The model of manifold with names of surface [5]

## 4. CONVOLUTIONAL NEURAL NETWORK (CNN)

This type of network has developed in recent years, and it makes possible solving computer vision tasks. This is because of a strong relationship between CNN and the brain's visual system. This network is characterized by local connections, scales, and local weights. Connections and weights enable the discovery of information patterns, while the last feature equips the network with the invariability of translations. The task of CNN is to analyze visual data and all activities with appropriate assignment of visual data, i.e. image classification, image segmentation, and even object detection [6].

CNN was designed to mimic the pattern of neuronal connections in the brain, and was inspired by the functionality of the visual cortex. The structure of CNN consists of a three-dimensional structure of neurons, which analyze different areas of the image. Each set of neurons specializes in a part of the image, and the final result is obtained using a forecast from the values representing the evaluation vector. This grading vector is intended to show the probability of a particular image feature belonging to a particular class. CNN consists of several types of layers:

- convolutional layer – a map of objects is created, on the basis of which class probabilities are predicted for each of the features,
- pooling layer – here the amount of data generated by the convolutional layers is reduced, and the most important data is preserved (the process of both of these values is repeated several times),
- fully connected input layer – data from previous layers are "flattened" to obtain a single vector needed as input information for the next layer,
- fully connected output layer – sets the steady probability of image class [7].

The CNN architecture is the most important factor influencing the operation and efficiency of the entire analysis process. There are many ways of building layers at the CNN and using relevant elements of the entire network. Figure 4 shows construction of the AlexNet network, designed for the SuperVision group. In comparison to other networks of this type, more filters are applied. It consists of five convolutional layers, followed by three fully connected input layers [7].

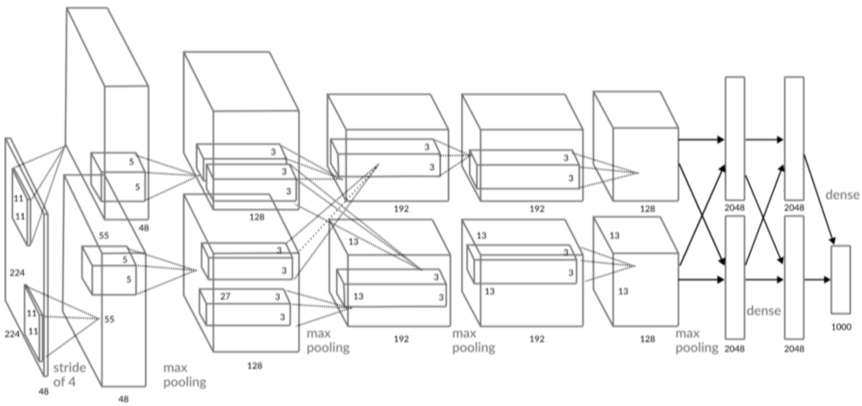


Fig. 4. AlexNet convolutional layer [7]

## 5. MODEL PREPARATION

Several essential tasks can be listed within the preparation of models based on convolutional neural networks. The first one is the proper workplace preparation, which involves downloading all the plugins necessary to work with the Jupyter Notebook environment. Another one is appropriate coding of individual commands, so that the whole allows for the implementation of neural networks with an indicated depth (among others) – ResNet networks. This part of the research is closely related to programming the software, which allows it to work properly, changes the variables that determine the learning of the program, saves and exports the results in easily visible forms.

The image recognition model may recognize images based on the previous information it receives in the form of photographs with or without the acceptability criteria. Therefore, it is necessary to prepare an appropriate database of photographs responsible for teaching the model what elements it should pay attention to. It is crucial that these photographs are taken in conditions as standardized as possible, as changes in the brightness of the photograph or the angle of the object in front of the camera may have a negative impact on the learning process. Figure 5 shows two elements, one of which meets the conditions of acceptability, and the other does not.

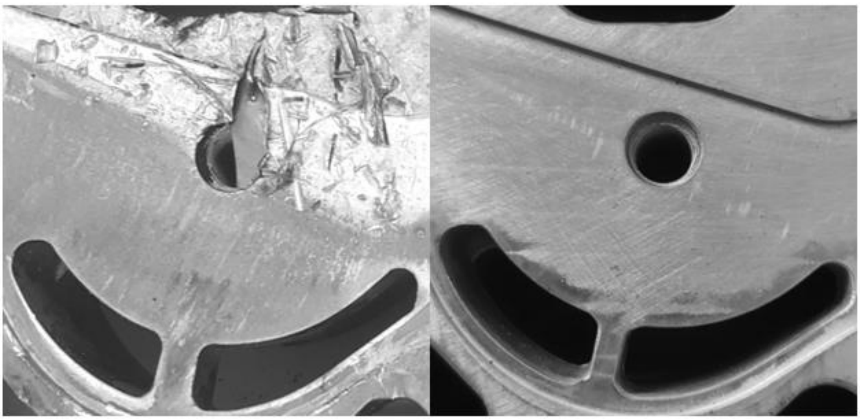

Fig. 5. Comparison of unacceptable defect (left side) with acceptable (right side) on the aluminum working surface

To understand the learning process, it is essential to know the types of images that affect model learning. There are three types of sets, two of which strictly affect the way the model is taught, and the third allows prediction based on a built neural network. These types are named accordingly:

- training set – the model learns on its basis,

- valid set – it allows to check whether a given mode is not overlearned and prevents algorithm overlearning,
- test set – pictures that the model did not see during learning are often called predicted.

It is also worth mentioning what does it mean that the model is overlearned. A properly functioning model can be flexible with the information it has received, i.e. understand all parameters in such a way that they can react appropriately to changes in photographs. An overlearned model means that the operation of the neural network focuses too much on the provided images, surpassing the effects of various parameters. This is reflected by the fact that the model seems to understand training images very well, while the performance of predicted assessments is significantly reduced. It happens because it focuses too much on the details that do not indicate a prediction for the relevant class.

The subsequent algorithm sequences refer strictly to model teaching. The main parameter is the ResNet parameter which determines the number of layers of the neural network. ResNet networks are deep convolutional neural networks, and the number at the end of the name indicates the number of layers it has. Selected Resnet networks that will be tested in model learning are as follows:

- ResNet-18 – pretrained neural network of 18 layers, usually used for simple defects; it can distinguish very well between, e.g., different animals, and the learning process of a model built on its basis is relatively short,
- ResNet-34 – pretrained neural network of 34 layers; just like ResNet-18, it is mostly used for less complex identifications, but has a greater number of values, so the learning process takes about 1.5 times longer than in ResNet-18 (with constant parameters: number of cycles, number of photographs, size of photographs, and others),
- ResNet-50 – pretrained neural network of 50 layers; it is widely applied as it can be very effective in assessing simple elements as well as more complex ones, and the learning process takes about 2.5 times longer than in ResNet18 networks,
- ResNet-152 – pretrained neural network of 152 layers; a network with the largest number of layers tested, usually used to recognize complex defects; the learning process of a model based on it takes up to 10 times longer than in ResNet-18 networks, but usually a smaller number of cycles is required to learn.

The method of importing a network together with a method of starting learning cycles is presented in the Figure 6. The examples of model learning values presented reflect three most important indicators of the assessment of neural network effectiveness. These are:

- train loss – an indicator about the theoretical error of assessment on the basis of a training set, on the example of value 0.520783 means 52% of theoretical learning error,

- valid loss – an indicator of theoretical error of assessment based on the created validation set; on the example of 0.366006 means 36.6% of theoretical learning error,
- error rate – an indicator about the expected error in the assessment of future photographs, which assumes the receipt of a similar quality of pictures, for example 0.2222222 means a 22% error in the assessment.

```
model = cnn_learner(data, models.resnet18, metrics=error_rate)
```

```
model.fit_one_cycle(6)
```

| epoch | train_loss | valid_loss | error_rate | time |
|---|---|---|---|---|
| 0 | 0.949043 | 1.234419 | 0.777778 | 00:14 |
| 1 | 0.805459 | 0.973164 | 0.777778 | 00:14 |
| 2 | 0.789604 | 0.588796 | 0.222222 | 00:14 |
| 3 | 0.692061 | 0.426967 | 0.222222 | 00:14 |
| 4 | 0.584972 | 0.366006 | 0.222222 | 00:14 |
| 5 | 0.520783 | 0.362635 | 0.222222 | 00:14 |

Fig. 6. Example of implementing cycle learning model

## 6. MODEL RESULTS

As it was already mentioned, the results are based on the use of four ResNet networks with different amounts of internal layers: ResNet-18, ResNet-34, ResNet-50, ResNet-152. Other parameters, such as the number of learning cycles, selection of the appropriate number of validation photographs, have been selected individually for each model in order to obtain the best results.

The results shown will be compared accordingly, separately for each of the defects. The main factor affecting the selection of the best ResNet network for each of the defects is the percentage rating of the prediction of photographs evaluated on the basis of the built model. In addition, consideration of theoretical error values, i.e. train loss, valid loss, and error rate will be provided.

### 6.1. SEALING SURFACE AT AIR DUCT

Figure 7 shows theoretical values based on individual models, which indicate that by far the best values obtained were achieved using ResNet-152. The second most promising result is obtained with the ResNet-18 network as it is characterized by low train loss and error rate, but the valid loss exceeds 30%. The worst theoretical parameters were obtained by ResNet-34 and ResNet-50 networks, where if the latter didn't exceed 55% of valid loss, it could suggest that the network has been properly taught. Such a high value may depend on possible mistakes in adjusting the learning parameters, or incorrect amount of input data for such a number of layers. In ResNet-34 network, high values of all parameters are affected, so it is probably not the right network for this type of defect.

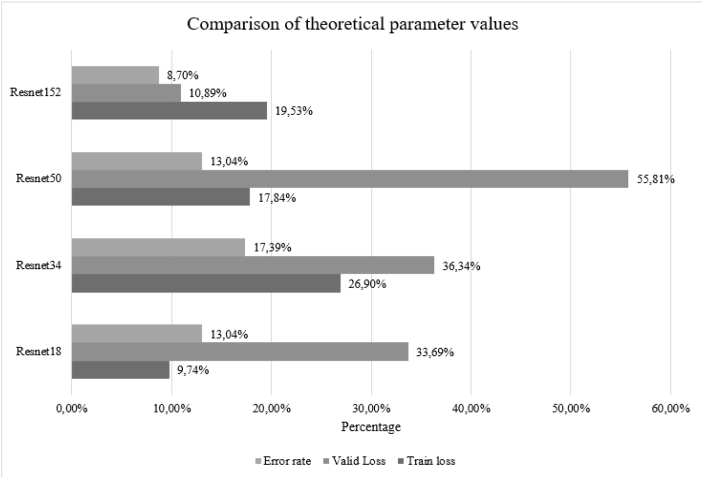


Fig. 7. Comparison of theoretical parameter values for air duct

The prediction results of individual models constitute an even more important comparison. This chart is presented in the Figure 8, and the indicators related to the relevant ResNet networks that can be observed are effectiveness in correct answers, average rating of individual decisions, the highest and the lowest value of each rating. All these values are presented in percentages, rounded to the nearest hundredth. Therefore, despite slight differences in the highest unitary rating, all of them reach 100%. Nevertheless, correct answers and an average rating of individual decisions are more significant than this value. While the same highest value for correct answers of 100% was obtained with ResNet-152 and ResNet-50 networks, ResNet-152 proved to be the best with 96.30% efficiency in the second indicator. It is a small difference between ResNet-34, where as much as 95.35% of the average rating of individual decisions was obtained, but an error occurred in the classification of one of the photographs. In the indicator of the lowest unit value of the decision, ResNet-152 with 70.83% efficiency proved to be unrivalled for other networks, surpassing the second ResNet-50 by over 16%. ResNet-18 network was definitely the worst in the whole comparison, showing the lowest values for all the most important indicators.

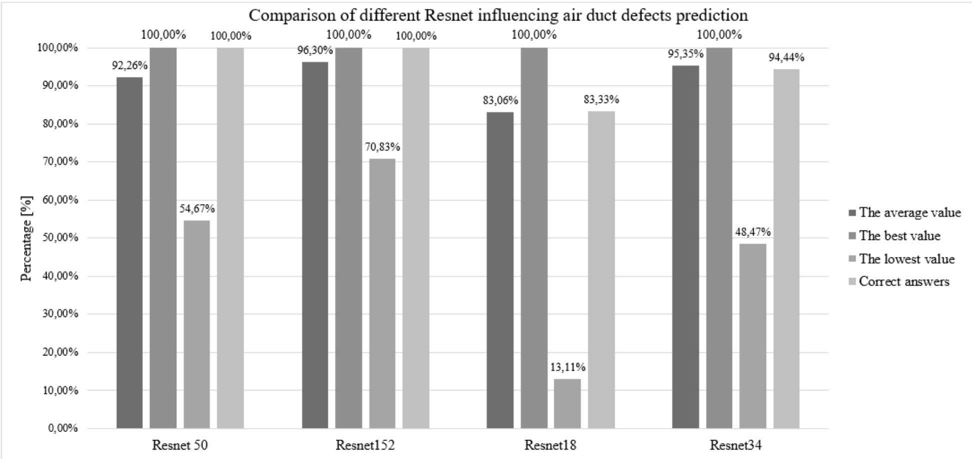


Fig. 8. Comparison of different ResNet influencing air duct defects prediction

When analyzing the results, it can be unequivocally stated that the use of ResNet-152 allows for the most accurate classification of defects arising on sealing surface at air duct. It can be influenced by the fact that they have complicated shapes and occur in different places. This can be noticed, e.g., in scratches that have different runs, depths, lengths, and can be tilted at different angles. All these factors may determine that the need for more layers is necessary in this case. In addition, this may be confirmed by the fact that the worst results of all were obtained by ResNet-18, although the parameters describing the neural network learning were relatively faultless. Apart from the visible improvement along with the increase in the number of layers in the results obtained during the prediction process, this indicates that for this defect, it is advisable to use neural networks with as many layers as possible.

### 6.2. ALUMINUM WORKING SURFACE

To perform a better analysis of the resulting indicators, parameters and results, all results were presented in the form of combined charts. The results referring to the theoretical parameters of the models including: train loss, valid loss, and error rate are shown on the chart in Figure 9. According to the information contained therein, the best-prepared model in theoretical terms is the model which uses ResNet-50 network, where the error rate was 0%, valid loss 7.12%, and train loss 13.22%. However, up to three models obtained a 0% error rate and this is in addition to ResNet-50, ResNet-34, and ResNet-152. Comparing these two, it can be stated that ResNet-34 seems to be better adapted with 23.9% train loss, by almost 16% lower than ResNet-152, with a relatively similar valid loss. Definitely the worst model is the one based on ResNet-18, with the highest values for most of these parameters. Based on this, three models can be selected that will most likely match the defects occurring on the aluminum working surface, and these are built with ResNet-34, ResNet-50, ResNet-152.

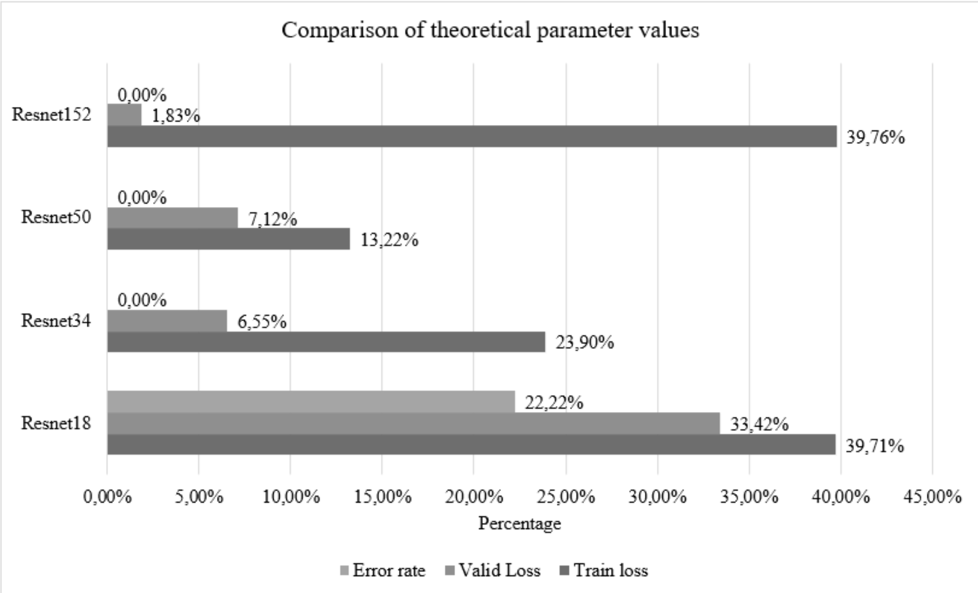


Fig. 9. Comparison of theoretical parameter values for air duct

The results of the prediction, presented in the chart in Figure 10, include four indicators: correct answers, average value, the best value and the lowest value. The best of them was achieved by ResNet-34 model with only one mistake in the classification of photographs. Definitely, it also has the highest score in the average individual decisions at 88%, with the second result of this type at 80%. It is clear that ResNet-34 model showed the best results during the prediction process, although the second best model is difficult to determine. All three other models have the same correct answer efficiency of 83.33%, and the average values do not differ significantly. The other two indicators, the best value and the lowest value, are not important in this comparison, as they also indicate similar results.

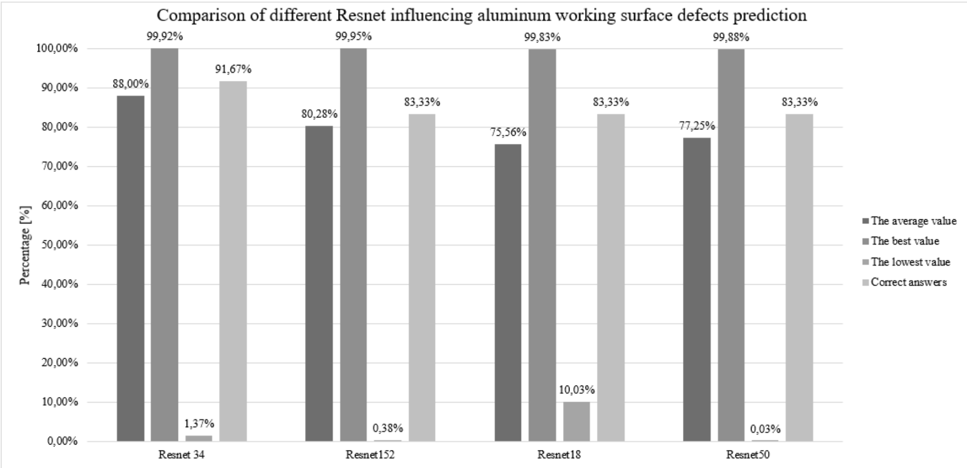


Fig. 10. Comparison of different ResNet influencing air duct defects prediction

When analyzing all the information presented in this section, significant differences in the prediction of acceptable and unacceptable manifolds in favor of the former can be noticed. This is an undesirable feature that might have many causes, but the simplest explanation is that the number of images based on which the neural network was taught is too small. The confirmation of this conclusion is that one of the defective images was always predicted as acceptable and the result of correct prediction did not exceed 11%. This means that the model was almost 100% convinced that this was a part suitable for remanufacturing.

## 7. SUMMARY

The presented analyzes and decisions related to the selection of the most suitable model for given surface defects are merely a suggestion, not a ready solution. Anyway, it can have a beneficial effect on, e.g., saving time. Under real conditions of implementing such a system it is necessary to use a much larger amount of input data and samples of predictive images, so that the results obtained can reflect their implemented operation as much as possible. With more photographs, on the basis of which the learning process of a given neural network is carried out, the extended teaching time of individual cycles is observed. A significant elongation in learning is therefore visible, and they differ in that the latter has 83 more pictures as input. It is imaginable how long it would take to prepare a model for which thousands of photographs would be prepared as input data. In connection to the suggestions regarding the most adaptable number of layers, preparation should start with a proposed model based on such neural network.

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# POPRAWA PROCESU REGENERACJI POPRZEZ METODY ROZPOZNAWANIA OBRAZU. ZASTOSOWANIE CZĘŚCI MECHANICZNEJ

**Słowa kluczowe:** *regeneracja, konwolucyjne sieci neuronowe, automatyzacja, ulepszanie, rozpoznawanie obrazu*

W artykule opisano możliwości wykorzystania, budowy i wdrożenia systemu rozpoznawania obrazu w firmie realizującej proces regeneracji. Artykuł powstał na podstawie pracy magisterskiej przygotowanej przy pomocy Wabco Reman Solutions. Przeprowadzone testy zostały wykonane na jednej z regenerowanych części w firmie - kolektorze. W badaniach skupiono się na różnych wariantach powstałych modeli rozpoznawania obrazów w celu dostrzeżenia różnic, które mogą wpłynąć na ich skuteczność i możliwość zastosowania w rzeczywistych warunkach pracy. Do budowy modeli, w których zaimplementowano konwolucyjne sieci neuronowe, wykorzystano środowisko Jupyter Notebook.