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Implementation of Machine Learning to Improve the Decision-Making Process of End-of-Usage Products in the Circular Economy

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Abstract

Rising consumption due to a growing world population and increasing prosperity, combined with a linear economic system have led to a sharp increase in garbage collection, general pollution of the environment and the threat of resource scarcity. At the same time, the perception of environmental protection becomes more sensitive as the consequences of neglecting sustainable business and eco-efficiency become more visible. The Circular Economy (CE) could reduce waste production and is able to decouple economic growth from resource consumption, but most of the products currently in use are not designed for the reuse-forms of the CE. In addition, the decision-making process of the End-of-Usage (EoU) products regarding the following steps has further weaknesses in terms of economic attractiveness for the participants, which leads to low return rates and thus the disposal is often the only alternative.

This paper proposes a model of the decision-making process, which uses machine learning. For this purpose, a Machine Learning (ML) classification is created, by applying the waterfall model. An artificial neural network (ANN) uses information about the model, use phase and the obvious symptoms of the product to predict the condition of individual components. The resulting information can be used in a downstream economic and ecological evaluation to assess the possible next steps. To test this process comprehensive training data is simulated to train the ANN. The decentralized implementation, cost savings and the possibility of an incentive system for the return of an end-of-usage product could lead to increased return rates. Since electronic devices in particular are attractive for the CE, laptops are the reference object of this work. However, the obtained findings are easily applicable to other electronic devices.

Keywords

Artificial Neural Network; Circular Economy; Classification; Decision-making process; Machine Learning; Remanufacturing; Reuse; Sustainability;

1. Introduction

Worldwide, one person generates on average 0.74 kilogram per day and the world generates 2.01 billion tonnes of municipal solid waste annually [1]. Furthermore, experts expect global waste to grow to 3.4 billion tonnes by 2050. Reasons for this enormous amount of waste are the increasing production and consumption of goods, caused by a growing population and increasing wealth as well as the low proportion of reused resources [2][3]. Consequently, the produced waste pollutes the environment and emissions lead to climate change. A way to reduce waste streams is reusing products or components and recycling of resources. The amount of resources needed to produce products increased significantly during the last years and is mainly covered by newly extracted resources [4]. During the last century, the focus has been on the production of goods from virgin materials [5]. Major improvements have been made in increasing resource efficiency instead of systematically designing out material leakage and disposal [6]. However, the awareness of society is shifting to environmental problems and lack of resources [5]. Rising standard of living with a simultaneously growing population can only be ensured in the long term through sustainable economic growth [7]. An opportunity to recover and reuse resources in order to reduce waste and improve sustainable use of resources is the CE.

1.1 Circular Economy and decision-making process

The CE replaces the ‘end-of-life’ concept of a common linear supply chain (SC). It supports reuse and use of renewable energy and tries to eliminate waste through superior design of the products and business models [6]. To this end, the concept goes beyond resource efficiency and productivity approaches and positions itself between pure efficiency approaches and schools of thought of sufficiency and post growth economics. Figure 1 illustrates the structure of the CE.

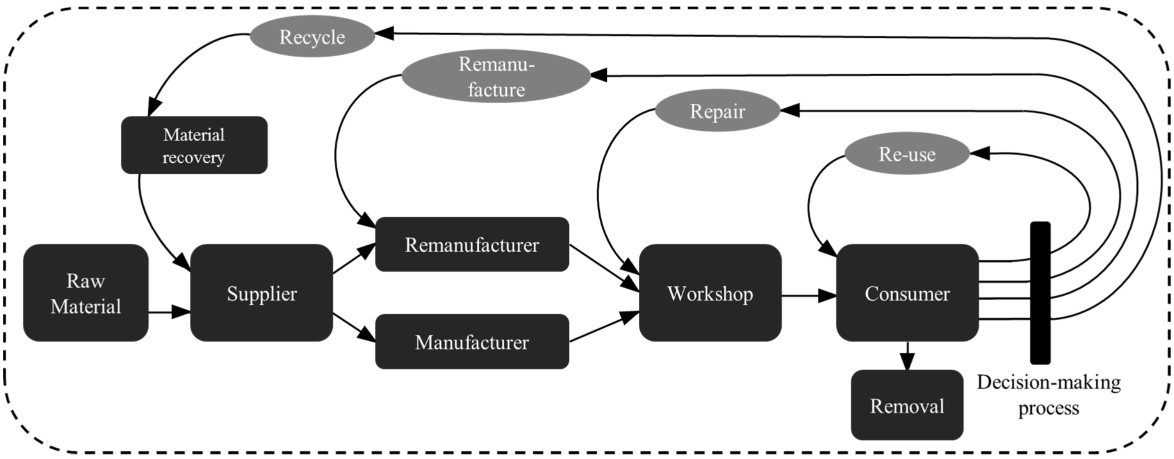


Figure 1: Structure of the Circular Economy. Own illustration based on [6][8]

In comparison to the linear economic system, there are more options than just disposal for an EoU product. It can be returned to the CE by different recovery options. An EoU product is a product that can be operative or inoperative. The owner can remove it or lead it to a decision-making process, which is represented by the black bar. It decides whether it is possible to lead the EoU product back to the SC and which is the preferred option. The inner circle is preferred of four main recovery options [6]. Recycling describes the least preferred, since it only recovers resources, which need energy to build a new product [9][10]. Remanufacturing is the process to disassemble the product to replace the defective components and worn out parts in order to achieve at least an as good as new condition. The customer gets a guarantee on the entire product [11][12][13]. Repair is similar to remanufacturing, except only the defective parts are replaced and the customer only gets a guarantee on this component [14][15]. Reuse is the preferred option, since the product is only reconditioned. This requires the least energy and the most resources are reused [6][16].

In the decision-making process various factors are considered. These can be divided into economic, environmental and social factors [17][18]. The economic factors are subdivided into recovery value and process costs. In order to compare the value of the recovered product to the costs to enable the recovery, it is crucial to evaluate the current condition of the EoU product. The total costs are mainly determined by purchasing costs and processing costs of the EoU product and the costs for the spare parts.

1.2 Problem and objective

A major problem regarding CE are the low return rates of the EoU products [8]. This superior problem has further partial problems as cause, which are listed in Table 1. Low resource prices compared to high labour costs resulting from manual examination of the EoU product, make new production more attractive than recovery. Short lifetime cycles and many different products lead to a complex decision-making process with frequent updates, which are difficult to implement at the different collection points. Economic success continues to be the driving force behind decision and investment. The recovery options are associated with a high degree of uncertainty, which is why many products are not returned to the SC and no investments are made in the circular infrastructure.

Table 1: Problems of the decision-making process

Problem	Literature
Low resource prices compared to labour costs and low automation level	[6][19]
Short lifetime cycles and many different products	[8][20][22]
Uncertainties of return	[3][14][22]
Complex decision-making process. Need of know-how with regard to disassembly	[11][19][20]
Missing preselection and infrastructure	[6][22][23]
Products are not designed for the CE	[9][24]
Missing attractiveness for owner of EoU product to lead it back to SC	[3][6]

In addition, the selection of the EoU products takes mainly place in central collection points and not upstream at the owner of the EoU product. This leads to unnecessary transports. Furthermore, most products currently in use are not designed for the CE. It is difficult to determine the condition and to refurbish these products. Most product owners choose the easiest way for themselves when a product reaches the end of its lifetime, which is in the most cases disposal. An incentive system and easier process could change this so that it is led to the decision-making process [23].

ML is already applied in various areas of CE. It is used for strategic decisions such as the product design, but also operational decisions, as estimating recovery costs. One example is the method developed by Goodall et. al. in 2015, which is a cost estimation for remanufacture with limited and uncertain information [20]. Jun et. al. have developed a method which determines the best possible recovery option by means of an evolutionary algorithm [25]. However, most methods assume that the condition of the EoU product is known, because the product is physically present at the decision-maker or using incomplete data. The focus is not on determining the condition of components of the EoU product in order to carry out a preselection.

The objective of this work is to develop a new decision-making process for the CE in order to increase the returning rates of laptops. The requirements of the new decision-making process are derived from the problems mentioned before. The decision-making process should be carried out as preselection at the customer in a decentralised form, but the expertise is to be developed and provided as a central system. In addition, an incentive system should be created for the EoU product owner to increase the motivation to return the EoU product. For this purpose, this paper develops a model to decentral determine the condition of a laptop. This can serve as a basis for an economic and ecological evaluation to select the right recovery option or for a cost estimation or selection method of best recovery option mentioned before. The model classifies selected components of the EoU laptop as defective or not defective by applying a ML based mixture of prognosis and diagnosis. Therefore, information is identified to determine the laptop condition and a possibility of capturing is defined to use them in the ML classification.

1.3 Methodology

The structure and methodology of this paper is based on the waterfall model, which serves software development. Figure 2 represents the steps to develop the laptop condition determination for the decision-making process. In contrast to the classic waterfall model, iterative interactions between various phases are possible here. After the problems to be dealt with and the objectives derived from them have already been worked out, this information is used to develop the decision-making process, which defines the system requirements. From these, the software requirements are derived in order to subsequently select a suitable one. The software selection is not covered in this paper. In the next step, the input variables and the output variables of the ANN are defined, as well as the structure and functionality. The information, which is defined for the determination of the condition of the component, forms the input. The output is the calculated condition of the component. The results are implemented in Microsoft Azure ML Studio. In order to finally test and evaluate the developed model, data is simulated beforehand.

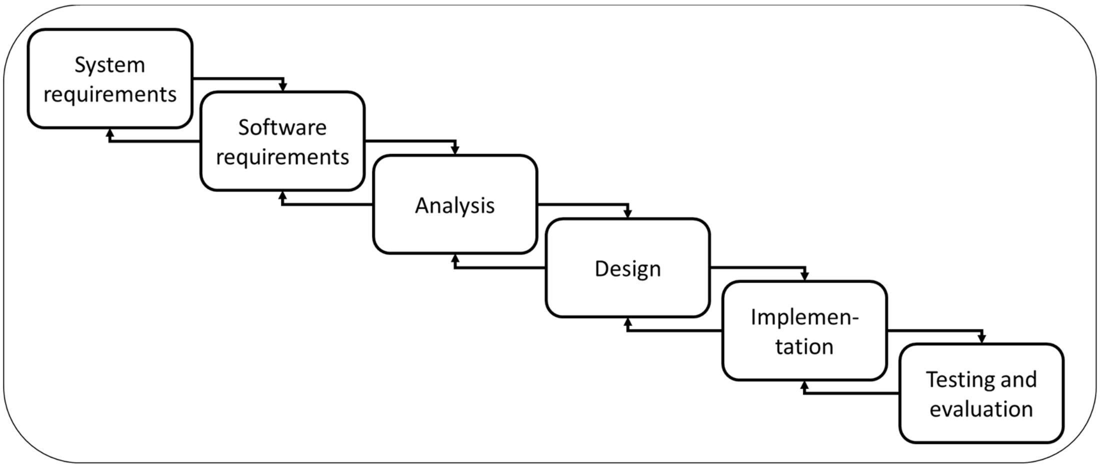


Figure 2: Waterfall methodology with iterative interactions. Own illustration based on [18], [26]

2. Development of the decision-making process

The problems and objectives defined in chapter 1.2 are used to model the decision-making process illustrated in Figure 3. In order to make it possible to carry out the process by the owner without sending the laptop to a collection point, only information is used which is easy to capture. Therefore, it has to be gathered without expertise, diagnostic tools and disassembly. Information of the laptop model and information about the use phase and external appearance are combined in order to determine the condition of defined components of the laptop. There is only a difference made between defective and functional. However, components are also assigned to the class defective if they should be replaced, since they only have a short service life. The condition of the components can then be used to conduct the economic and ecological evaluation of the recovery options in order to select the best.

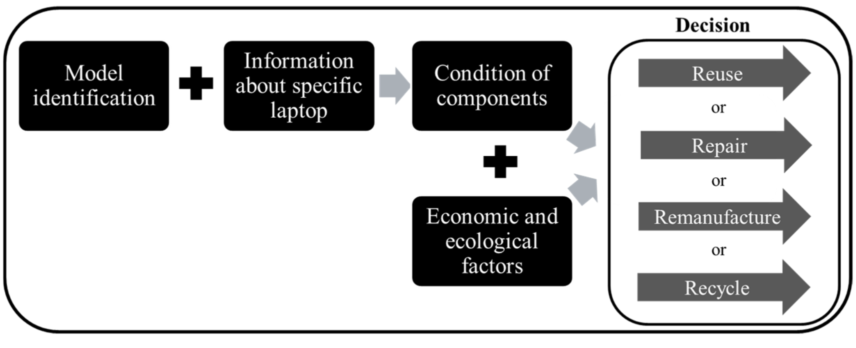


Figure 3: Decision-making process

As part of this work, 10 components are selected, of which the condition will be determined. These are susceptible to wear or have a high value and thus have a high relevance for the evaluation of the laptop. The components are battery, CPU, GPU, display, keyboard, mousepad, motherboard, outer casing, hard drive and cooling system. First, the stress factors are determined, which have an impact on the condition of laptops. Figure 4 shows the stressing factors in the left table. Most stressing factors cannot be detected without installation of sensors and the use of software. The laptop should not be upgraded before usage, since the model should also work for laptops, which are not designed for the CE. Therefore, information is selected which is easy to gather at the moment of evaluation, but still provides information about the stressing factors during the use phase. Figure 4 shows the information, which will be used as input for the ANN, in the right table. It is not possible to record information concerning all stress factors. The focus is on usage intensity and temperature.

Stress factors [27]
Temperature
Humidity
Dust and dirt
Radiation
Acceleration
Bending and pressure
Current
Voltage

Defined information for determining condition
Brand
Model
Price
Age
Type of usage (categories)
Mobile usage
Usage of laptop bag
External damages of 6 external components (categories)

Figure 4: Stressing factors and defined information for determining conditions

The brand, model and price provides information about the quality of the components and the construction of the laptop. This has an influence on wear, fall damage and the ability to dissipate heat. Age is related to usage time and components installed. The type of usage can provide information about how intensively the laptop in general and certain components were used. Therefore, the categories surfing, business, computational intensive, gaming and videos are defined. A laptop in mobile use is exposed to more dust and higher risk of falls. Accumulated dust in the ventilation reduces the ability to dissipate heat and therefore causes higher temperatures. A case protects the laptop from dust and fall damage and can also be an indication of how carefully the laptop was handled. External damages to the laptop can also be easily captured by the owner. Therefore, these are recorded and assigned to one of six defined locations of the laptop. There are different damage classes for each of the six locations. Damages to different locations can have different influences on individual components of the laptop. The information described (see right table of Figure 4) is used as independent variables of the classification process and serves as input to the ANN. The 10 components are the dependent variables and form the output.

The ANN is chosen as the ML method as it is very powerful in classification applications. It can uncover many complex correlations in data sets and process different inputs. Moreover, the hardware costs incurred for the supply of computing power have fallen significantly in recent years. Since the application considered here is a mixture of prognosis and diagnosis, a feed forward ANN is applied.

3. Data simulation

In order to train and evaluate an ANN, comprehensive data is required. This is simulated in RStudio following the procedure shown in Figure 5. Sixteen exemplary models are defined and 250,000 objects are created from these. The model clearly defines the brand and price. In addition, each object is assigned an age by means of a normal distribution, which has a mean value of 36 months and a standard deviation of 8 months. Each model has different probabilities that the object will be assigned to one of five defined usage types. In order to simulate the dichotomous variable of mobile use, the Monte Carlo approach is applied. The probability of mobile use of the laptop is calculated based on the model and the type of use. This is then compared to a random number (between 0 and 1) to determine the value. The calculation of the variable "use of case" is analogous to this. The value of the six variables, which describe the external condition, is then simulated for each object. This is done by only using probabilities for the error classes and is independent of the values of the other variables. Finally, the dependent variables are calculated for each object. For each of the 250,000 objects and for each dependent variable a probability is calculated that the regarding component is defective. This is done by means of logistic regression function, as it provides values between 0 and 1. Here the correlations between input and output are implemented by defining the weighting factors, which determine the influence of independent variables and characteristics of variables. For example, a cheap laptop ages faster than an expensive one or a gaming laptop stresses the CPU and GPU more intensive. By applying the Monte Carlo approach again, it is determined whether the component is has to be replaced or not.

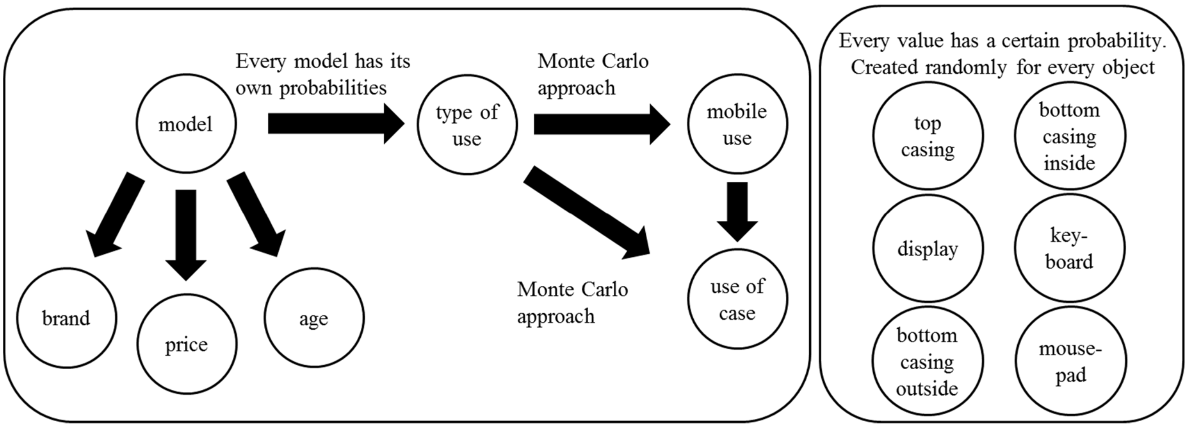


Figure 5: Simulation of independent variables

4. Implementation of neural network

After the requirements for the neural network have been defined and the data simulated, the neural network is now implemented in Microsoft Azure ML Studio. Figure 6 illustrates the process. Since a separate ANN must be trained for each of the ten components, this process is conducted ten times.

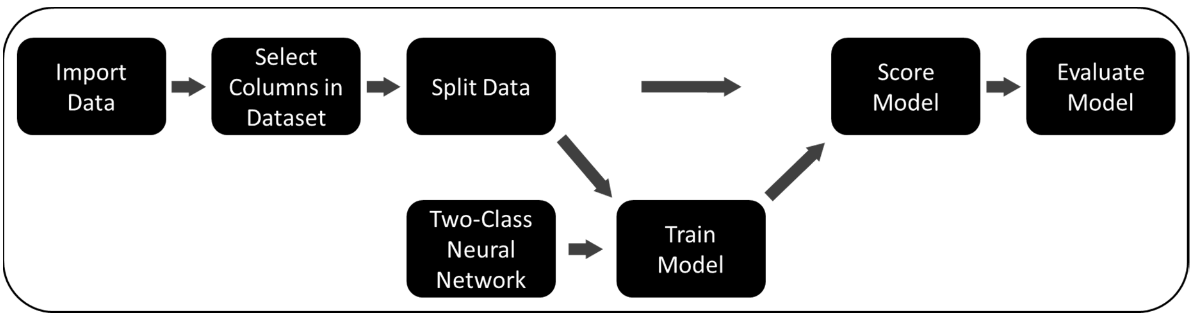
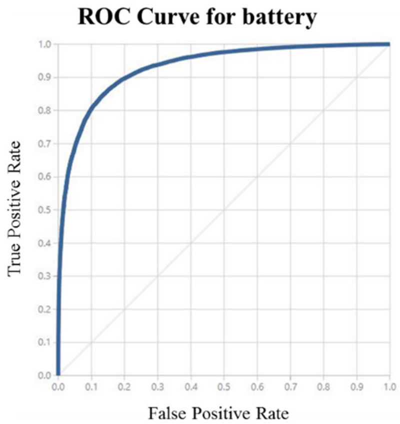


Figure 6: Process of creating the artificial neural network

After importing the simulated data, the independent variables and the respective dependent variables are selected. It is determined which variables are used to determine the condition of which component. The 250,000 data sets are subsequently divided into training and test data. Literature recommends a value of 80% training data [28]. Furthermore, the desired Two-Class Neural Network is selected as ML method. In addition, the structure is defined. The hidden layer specification is set to fully connected and the number of hidden nodes to 100. This means that each of the input neurons (independent variables) is linked to all neurons of the hidden layer, which are connected to the output neurons (defect or not defect). The next step is to train the created neural network with the training data. For this it calculates an output based on the input. This is then compared with the correct solution, which is why the method applied here is called supervised learning. By the determined error value, the configurations in the ANN are adapted in order to reduce the error value. This process is repeated for all data sets. In the next step, the trained ANN calculates the solutions for the test data. In the last step, the results obtained are compared with the actual solutions in order to evaluate the model using different metrics.

5. Results

Microsoft Azure ML Studio provides metrics, which evaluate the developed models. Figure 7 illustrates in the left hand side exemplary the receiver operating characteristics (ROC) curve of the battery model and in the right hand side metrics for all models.



Component	AUC	Threshold	Accuracy	Recall	Precision
Battery	0.930	0.25	0.859	0.849	0.652
CPU	0.953	0.25	0.927	0.851	0.695
GPU	0.941	0.25	0.936	0.719	0.678
Display	0.973	0.45	0.929	0.851	0.854
Keyboard	0.983	0.5	0.956	0.870	0.885
Mousepad	0.942	0.25	0.925	0.731	0.673
Motherboard	0.932	0.25	0.902	0.713	0.669
Housing	0.964	0.25	0.921	0.848	0.716
Hard drive	0.887	0.25	0.887	0.610	0.508
Cooling system	0.940	0.25	0.883	0.817	0.717

Figure 7: ROC curve of the battery model and metrics for all models

The ROC is used to evaluate the performance of classification models in ML. It provides the area under the curve (AUC), which describes the ability of the model to separate the calculated values of the two output options. Figure 7 shows that the AUC is well above 0.90 for all models except the hard drive, which is a very good value. Furthermore, the accuracy is listed, which shows how many of the test data sets are determined correctly. The recall is the fraction of all defective data sets, which are labelled as defective. The precision is the proportion of true results of all as defective labelled data sets. A distinction of the errors is meaningful, since these have different consequences. For the system considered here, recall is the most important metric because the error that a defective component is considered as a functional one is the most serious error. This would lead to a laptop being purchased at a higher value than it actually has and would lead directly to a loss of money. The error that a functional battery is considered to be defective is not so bad. This would lead to the laptop being assigned a lower value than it actually has. Only possible turnover is lost as a result but not the own money. Therefore, the precision and accuracy is subordinated to recall in this case. The recall value can be increased by lowering the threshold value. However, this leads to a decrease of accuracy and precision. The threshold is set so that it does not fall below a value of 0.25, that not too many objects are considered as defective. It is also chosen as high as possible while ensuring a recall of 0.85, in order to purchase many EoU laptops. The recall values show that the defective objects of some components are detected very well. However, for those below 0.80, the model should be further improved by using more independent variables or implementing a manual check for objects of which the calculated value cannot be clearly assigned to defective or not defective.

6. Conclusion

The developed ML classification for determining the condition of EoU laptops can significantly improve the decision-making process in the CE, especially for products, which are not developed for the CE. The developed procedure, which collects information on stress factors via indirect relations to process it in an ANN, offers great potential for products that cannot be equipped with sensors. Its decentralized application saves costs for infrastructure and unnecessary transports. In addition, the return of EoU products becomes significantly more attractive, since the information obtained can be used to carry out an economic evaluation. This means that the owner can be offered a price for the EoU product. Since the condition of the product is determined at component level, the costs incurred for repair can be determined more precisely. Without the laptop being physically present, it is possible to determine to a certain extent which repairs are required. This increases the safety of the purchases of EoU products and thus also the number of recovered products. In addition, an ecological evaluation is made possible. The emissions generated during the production of a new laptop can be compared with the emissions generated during the production of the required spare parts for the recovery. In addition, the information gained offers further potential. Conspicuous features in the data sets can be used to improve product development. Furthermore, information regarding the number and models of returning products can be used for sales forecasts.

Because the classification is centrally hosted, it is much more flexible and cost-effective. New product generations or product types can easily be integrated and significantly more data is generated and collected. This is important, since the more complex the ANN gets, the more data is required to train it. Therefore, further possibilities must be investigated in order to implement more products and information in the process without increasing the complexity too much. This includes the generation of information categories, which would significantly reduce the number of input neurons. An example would be to only record the brand instead of model or summarizing models with a similar type of construction or price segment.

By applying ANNs, it is possible to uncover relations between the describing variables and the condition of the laptop, which one does not suspect. Therefore as much data as possible should be collected. The increasing number of sensors in devices in the progression of the Internet of Things will have a supporting effect. In future, further sensors and software should be implemented in the development phase of electronic devices in order to be able to better determine the condition of the product.

As the results show for certain evaluation values, considerations must be given to adapting the model or checking a component manually by first sending in the laptop before signing a sales contract, if the calculated value of the ANN is close to the defined threshold and so it could be defective or functional. Where possible, the existing temperature sensors and the already implemented components utilization (CPU and GPU) should be used. This requires a pre-installation of software and would make the model more complex, but could significantly improve the results of the classification. In addition, it must be noted that in this work the data are simulated on the basis of own knowledge and estimations. The reality is much more complex, which can lead to change in the results.

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Biography

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