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Combining Computer Vision, Artificial Intelligence, and 3D Printing in Wheelchair Footrests Design Customization: The KYKLOS 4.0 Approach

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Abstract: In the current paper, we present our work toward developing a solution combining computer vision and artificial intelligence (AI) to support footrest design customization in the wheelchair industry. Wheelchairs and postural systems are complex and often user centric in the design process. Those products require a wide range of adjustments to adapt to the various anthropometries and disabilities of patients. Most commercial products, dedicated to severe disability, also include a series of additional elements, designed to keep the patient in a comfortable but "fixed" position. Such systems do not allow to "fix and maintain" the position of patient foot, especially for patients who have no control over their lower limbs. For that reason, it becomes essential to supply wheelchairs with specific elements to hold patient's shoe in place. Commercial foot supports are typically developed on standard sizes and do not always cover the entire population. In addition, those designs are based on standard shoes; thus, they do not lend themselves well to adapting to special shoes or orthopedic shoes. Feet final position therefore becomes a key element in correct postural management. In this paper, we investigate the use of computer vision and AI to correctly define customization parameters of the footrest. The proposed design has been developed based on the specifications received from the Pro Medicare S.r.l (https://www.promedicare.eu/en/) orthopedic technicians. We present suitable algorithms, design principles, and well-defined components toward the implementation of our proof of concept. We also present the testing activities we have undertaken and the obtained performance results.

Keywords: additive manufacturing, artificial intelligence, deep learning, design customization, wheelchair, footrest, KYKLOS 4.0, circular economy

1. Introduction

Additive manufacturing (AM), also known as 3D printing or rapid prototyping, is one of the most appealing aspects in industry 4.0 since it promises a radical transformation to industrial production by enabling the creation of lighter, stronger parts and systems [1]. AM is expected to gain more and more momentum in the future, thanks to the advantages that it offers over traditional manufacturing. Cost reduction, time efficiency, and customization of products with complex geometries seem to be the main aspects driving the rapid deployment of AM in production environments [2]. Unfortunately, variability in products quality and process reliability remain a big challenge that needs to be addressed [2]. The use of artificial intelligence (AI) in the context of AM is still being explored by academia and industry. The related use cases cover the entire production life cycle and range from design recommendation, through defect detection, to predictive maintenance.

Designing and producing wheelchairs are a big challenge since it is expected that this wheelchair will offer appropriate seating and postural support without compromising important aspects such as strength and safety (https://www.ncbi.nlm.nih.gov/books/NBK143784/). For this reason, recent research work has been particularly focusing on making the wheelchairs smarter. Arshad et al. [3] have developed a system to convert a manual wheelchair into an electric one. This system uses appropriate sensors and prescribed machine learning (ML) algorithms incorporated into the wheelchair seat to detect patient' real-time sitting positions to avoid diseases. Liyao [4] explores the life needs of patients with amyotrophic lateral sclerosis (ALS) and the nursing needs of nursing staff. Their solution uses AI in the design of wheelchairs dedicated to ALS patients and aims at providing intelligent methods and paths for the rehabilitation and care of these patients. Liu et al. [5] propose a solution enabling, for instance, patients to use intelligent wheelchairs for arranging order and time of

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hospital visits, automatically positioning and navigating within the hospital, and sending patients to the examination location.

Wheelchairs (Figure 1, left) are composed of a series of elements designed to be adjusted and adapted to the various anthropometries and disabilities of patients. Most commercial products, dedicated to severe disability, also include a series of additional elements, designed to keep the patient in a comfortable but "fixed" position. Postural pads and belts are typical elements used on cushion backrest. Feet final position therefore becomes a key element in correct postural management. Most wheelchairs have fixed or foldable planar footrests as showed in the following picture.

Figure 1
(Left) Standard footrest design. (Right) Example of a footrest designed by KYKLOS 4.0

Such systems do not allow to "fix and maintain" the position of patient foot, especially for patients who have no control over their lower limbs. For that reason, it becomes essential to supply wheelchairs with specific elements to hold patient's shoe in place. Commercial foot supports are typically developed on standard sizes and do not always cover the entire population. In addition, those designs are based on standard shoes; thus, they do not lend themselves well to adapting to special shoes or orthopedic shoes.

Based on these considerations, we decided to exploit AI to correctly define customization parameters of the footrest (Figure 1, right). The proposed design has been developed on the basis of the specifications received by orthopedic technicians from the company Pro Medicare S.r.l (https://www.promedicare.eu/en/). The system consists of a base that can be fixed by screws to standard footrests already provided in the wheelchair, and its design provides two vertical walls, conformed to the shape of the shoe, which stabilize and firmly maintain the heel and sides of the shoe.

Once the customization parameters are computed, this information will be communicated to a 3D modeling engine that will adapt the CAD model and consequently to the 3D printer to produce the footrest. The main goal of this new approach is to simplify the procedure to obtain best fitting design.

2. Related Work

Although the use of AI in the context of AM is still in an exploratory phase, the use cases that have been demonstrated so far by academia and industry seem to be promising. The manufacturing stages where the AI applications were proposed cover the entire AM life cycle.

The AI research company EMERJ [6] has explored the potential use of AI in AM and found that the related applications span the following four segments [7]:

1. Improving efficiency in the prefabrication stage: Here, a user willing to manufacture a given part takes the CAD files describing this part as well as the desired output and check whether AM is suitable for processing the production. In the context of generative design, ML can be in particular used for generating and evaluating digital models that will be used in the 3D printing production.
2. Defect detection: An AM technology, like any other, is prone to defects. This means the part that was produced from 3D printing could reveal some aberrations. In order to detect such failures and discard the concerned parts, computer vision and AI can be utilized. Here, the printing process will be inspected through high-resolution cameras, and suitable machine leaning algorithms will be used to match the recorded patterns to well-known defects in the AM technology.
3. Real-time build control: The idea here is to take defect detection using computer vision and dynamically control 3D printers to compensate for the defects. This approach will certainly help in limiting waste of time and materials.
4. Predictive maintenance: According to Fortune Business Insights [8], the 3D printing industry market size that was US$ 10,41 billion in 2019 could reach US$ 54,96 billion by 2027. An important segment in this market is the spare parts industry [9]. Concretely, 3D printing is offering many benefits to this industry including less production costs, 3D digital inventory (printing parts on demand), and faster delivery time. ML and predictive maintenance will also play a crucial role in the expansion of this segment. For instance, applying ML to predict in an accurate way the remaining useful life of a certain part can help in scheduling an appointment for the part replacement.

Jin et al. [10] reviewed ML methods used in AM and divided the different approaches into three categories: geometrical design, process parameter configuration, and anomaly detection. In the area of geometric design, AM enables the construction of complex lattice structures with different material distributions that meet the requirements of the respective application. In the part process parameter configuration, the authors address the work that uses ML methods to influence the quality of the final printed products through the choice of process parameters. In addition, justifications for the use of ML are provided, as well as recent literature such as Fera et al. [11] and Zhang et al. [12] on the application of ML to optimize and interpret the analytical relationship between process parameters and product quality. Finally, the authors address the approaches (computer vision methods, improved test setups, and novel simulation approaches) that deal with the detection of anomalies in the manufacturing process (detection of defective ones). These methods aim to assess the printing condition and product quality efficiently and accurately.

The use of ML in AM was also discussed in detail in Razvi et al. [13]. The authors analyzed 50 papers, identified where and how ML techniques were applied to AM, and organized in an easy way the obtained findings. The approach followed by the authors partially overlaps with the one discussed previously by EMERJ. Here, the use of ML was explored through all the production lifecycle stages, namely design, process planning, building,

post-processing, and testing and validation [13, 14]. Within each stage, a variety of functions can be implemented using ML techniques as it is shown in Table 1; the implemented techniques are used, for instance, for prediction, performance optimization, defect detection, classification, regression, or forecasting [13, 15].

In this paper, the use of ML for AM falls within the "design" stage and under the "design recommendation" function (see Table 1). However, the context is completely different. In Yao et al. [16], ML was used to assist inexperienced AM designers by offering them an automated AM design feature recommendation method. The latter combines hierarchical clustering (unsupervised learning) and support vector machine (SVM) (supervised learning). Other researchers [17, 18] have used various neural networks (NNs) techniques to help designers estimate build time factors for instance. In KYKLOS 4.0, a ML-based solution was developed to predict some anthropometric measurements needed for the design of the footrest of the wheelchair. The solution is customer/user friendly since it only requires a picture of the contour of the shoe of this person. Here, computer vision and NNs are combined to predict the length, top width, and the bottom width of the footrest. The generated information is sent then to the 3D modeling component to further design this part.

3. Wheelchair Design Support: The KYKLOS 4.0 Approach

To be able to accomplish the proposed workflow to produce personalized products using additive manufacturing, the collaboration of various components is required. The functionality introduced by the DL Toolkit, a Data Analytics Enabler component in its essence, is leveraged to support the functionality of the KYKLOS 4.0 Smart Design Enablers.

In fact, a specific part of KYKLOS 4.0 Project is focused on mass customization through the development of a product parametric design methodology able to collect input data from anthropometric measures, design constraints, and producer expertise and to automatically process and translate them for using

as design inputs for dimensioning a 3D parametric model of the customized product. The entire workflow includes the best definition of variables (dimensions) that should be used as inputs for the final product configuration, the usage of a 3D parametric model in order to create a custom part, and the introduction of specific tool to simplify procedure and measure of custom parameter. Specific components developed within this project, as listed below, are closely connected to the DL Toolkit and allowed the definition of customizable products such as the footrest design:

- **Parametric Design Methodology by CETMA**: This component was specifically developed in order to transform anthropometric dimensions into custom parameters for the wheelchair production. This methodology also defines which are the main important dimensions that should be extracted by the DL Toolkit through the image contour analysis. The output of this approach will be a solution that could be applied to create product parametric design engine. The analyzed workflow includes the best definition of variables (dimensions) that should be used as inputs for the final product configuration, the usage of a 3D parametric model in order to create a custom part, or a custom assembly, based on provided inputs. Thanks to this methodology, and guided by Pro Medicare technicians, we were able to define a set of variable to determine the footrest correct parametrization. This approach could be used for mass customization, thanks to the use of both the DL Toolkit and the Web 3D Modeling component.
- **Web 3D Modeling Component by TWI**: The Web 3D Modeling component receives the extracted dimensions as input (Figure 4). Using the functionalities provided by the Web 3D Modeling component, a watertight CAD model of the footrest is automatically generated. This tool is based on scripting modeling that is able to drive the design of a 3D model, using a set of independent variables. In this case, these variables are the extracted dimensions presented in this paper. The footrest design is built in a way to be able to be automatically exported in a watertight 3D printable format

Table 1
Overview of ML algorithms used in AM applications

Production stage	Implemented functions	Examples of ML techniques used
Design	• Design recommendation • Topology optimization • Tolerancing and manufacturability assessment • Material selection	Hierarchical clustering, SVM, NNs, genetic algorithms
AM process and performance optimization	• Predicting process response • Predicting property and performance response • Process parameter determination • Process optimization	Self-organizing maps, back propagation NN, Gaussian process regression, polynomial regression
IN-SITU process monitoring and control Post-process monitoring and control	• Anomaly/defect/failure detection • Machine condition monitoring • Real-time process control • Detecting cyber physical attacks	KNN, Bayesian classifier, PCA, SVM, spectral CNN
Quality assessment	• Product inspection • Testing and validation • Surface metrology • Defect detection and classification	KNN, decision tree, augmented layerwise spatial log Gaussian Cox process (ALS-LGCP)

and pushed for manufacturing via AM by just receiving input from the DL Toolkit. This can be done rapidly to provide different configurations of the footrest template and conform to a variety of patient characteristics (i.e. different shoe size, shape, etc.). An example of generated footrests can be seen in Figure 2.

The footrest models presented in the above figure are exported in both .stl and .step format to be either directly 3D printable or editable in other CAD software. A key factor to enable the generation of highly personalized models is the utilization of web collaboration tools. The Web 3D Modeling component has been developed in a way that it can be accessible through the web. The patients are able to access the tool, upload a picture of their shoe contour traced in a piece of A4 paper, and then further process the

generated 3D model. The overall workflow for the AI-driven design of the footrest is presented in Figure 3.

By using the design principles dictated by the parametric design methodology, we developed a framework for providing personalized products such as the footrest component. In the heart of this framework lies the scripting modeling language CADQuery. The footrest component has been designed following an algorithmic approach that enables the generation of the footrest component as an output of a constraint-driven function. The CADQuery script receives as input the independent variables of the design and generates the corresponding personalized design according to the input received.

The constraints set by the anthropometry of each specific patient regarding his/her shoe can be summarized by the following two parameters, (i) shoe length and (ii) shoe width. Therefore, our design would need to accurately cover each combination of the aforementioned parameters. To be able to implement the above

Figure 2
A series of footrests generated by the 3D modeling component
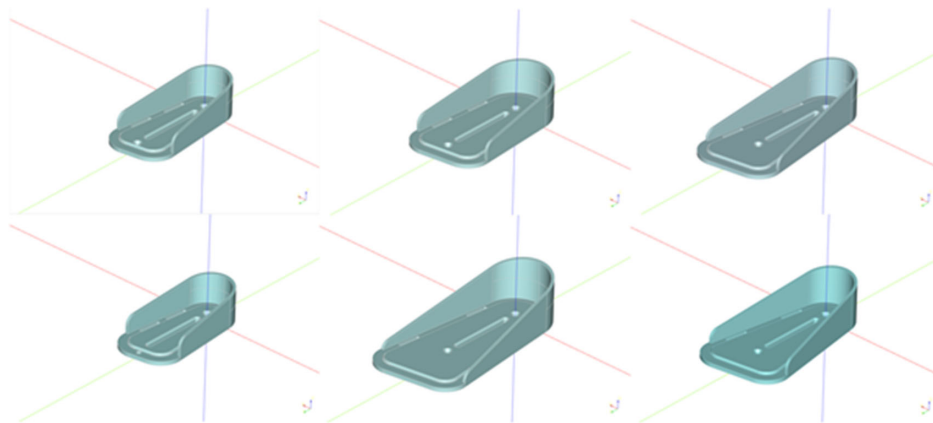
Figure 3
Personalized footrest value chain. The design process begins with a contour of the patient's show, and the associated anthropometric dimensions are extracted, which then drive the design of a parametric footrest CAD model
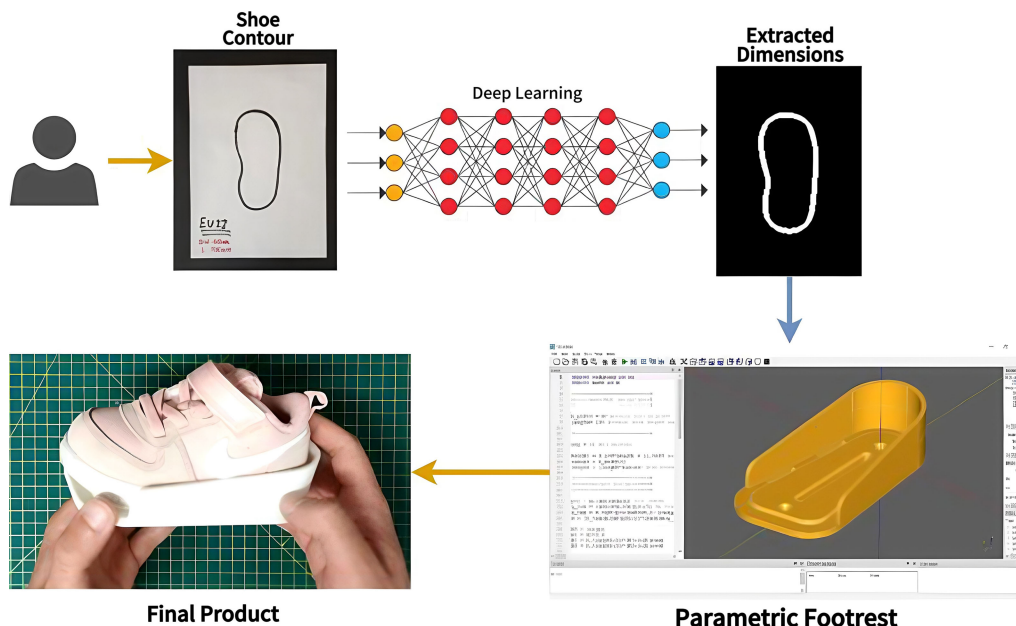
Table 2
Shoes samples

(No. of samples = 24)	Length	Top width	Bottom width
Max	275 mm	110 mm	85 mm
Min	135 mm	65 mm	48 mm
Average	216 mm	86 mm	64 mm
Median	222 mm	88 mm	65 mm

Table 3
Examples of good and bad taken images

Example	Taken image	Description
1		Scan image is ***perfect*** The shoe is placed up *straight* in the *center* of the image. It was taken with a scanning device, the *lines are clean* and visible Name: img_174_75_60_t.png
2		Image is ***very good*** The background shows a *good contrast*, the *entire A4 sheet is visible* and the shoe is properly marked. The shoe is not perfectly lit, but that is okay Name: example_276_115_88_f.jpg
3		Image is ***very good*** The background shows a *good contrast* and the *entire A4 sheet is visible*. The lines were drawn with a *pen* Name: example_276_115_88_f.jpg
4		The image is ***not good*** We took this image with a *noisy background*. It interferes with the current implementation of the software The image does have good lighting, which is good
5		The image is ***not good*** The drawing is great, but there is *no contrast* between A4 sheet and *the white background*

constraints in our design, the following parameters to use as independent design variables are received as input from the parametric design methodology, the (i) heel radius – r, the (ii) shoe length – L, and the (iii) footrest angle – ϕ. The anthropometry of the patient, as well as the design variables, is presented in Figure 5.

The user input (i.e. shoe contour), inspection of the generated model, further processing, and export for 3D printing are all implemented inside the Web 3D Modeling component of the KYKLOS 4.0 Project. The interconnections between the front-end interface, DL Toolkit, and CADQuery script enable the generation of virtually infinite number of personalized products through a user-friendly interface. An example of generated footrest, as well as further processing controls, is presented in Figure 6.

4. Footrest Design Support

4.1. Overview

The footrest design is supported by using a streamlined dimension extraction of the footrest. This is done by using a computer vision component to extract the dimensions of the contours of the shoe on an A4 sheet of paper, followed by using a ML component trained to rectify the computer vision biases as opposed to the dimensions measured by hand.

1. Contours of a patients' shoe are drawn on an A4 sheet of paper and photographed (Tables 2 and 3).
2. The model extracts the dimensions of an object using OpenCV (OpenCV is a computer vision library with which we can extract the dimensions of an object from an image if a reference object with known dimensions exists in the image)
- Computer vision-based extraction of shoe length from an image
- Computer vision-based extraction of top shoe width from an image
- Computer vision-based extraction of bottom shoe width from an image.
3. It uses the dimensions found by OpenCV and feeds them into a ML model, which predicts the anthropometric measurements of the patient's shoe.

Figure 7 gives an overview of the overall structure of the implementation.

4.2. Computer vision component for the footrest design support

The footrest design is supported by using a streamlined dimension extraction of the footrest. This is done by using a computer vision component to extract the dimensions of the contours of the shoe on an A4 sheet of paper, followed by using a ML component trained to rectify the computer vision biases as opposed to the dimensions measured by hand.

The second step described in Figure 7 requires a step, wherein an A4 sheet is detected within an image and cropped out. The current implementation draws the contours of the image and then extracts the largest A4 sheet-shaped object in the image as shown in Figure 8. The A4 sheet extraction takes place to be able to have a reference when attempting to evaluate the shoe contour dimensions.

The computer vision component also has three extraction respective methods with which the three individual shoe contour dimensions are evaluated:

- Length extractor: the length extractor (Figure 9) is a function that fits a linear line to the contour, finds its intersections with the shoe contour, and evaluates the pixel distance between the top and the bottom pixels. This value is then divided by the density of the image (pixels per millimeter square), which can be calculated when one considers the dimensions of the A4 sheet.

Figure 4
This figure shows how the 3D model is generated from the received anthropometric measurements. Running in the back, a Python script running in the environment of CADQuery library receives as input the extracted dimensions and generates a watertight 3D model of the footrest component
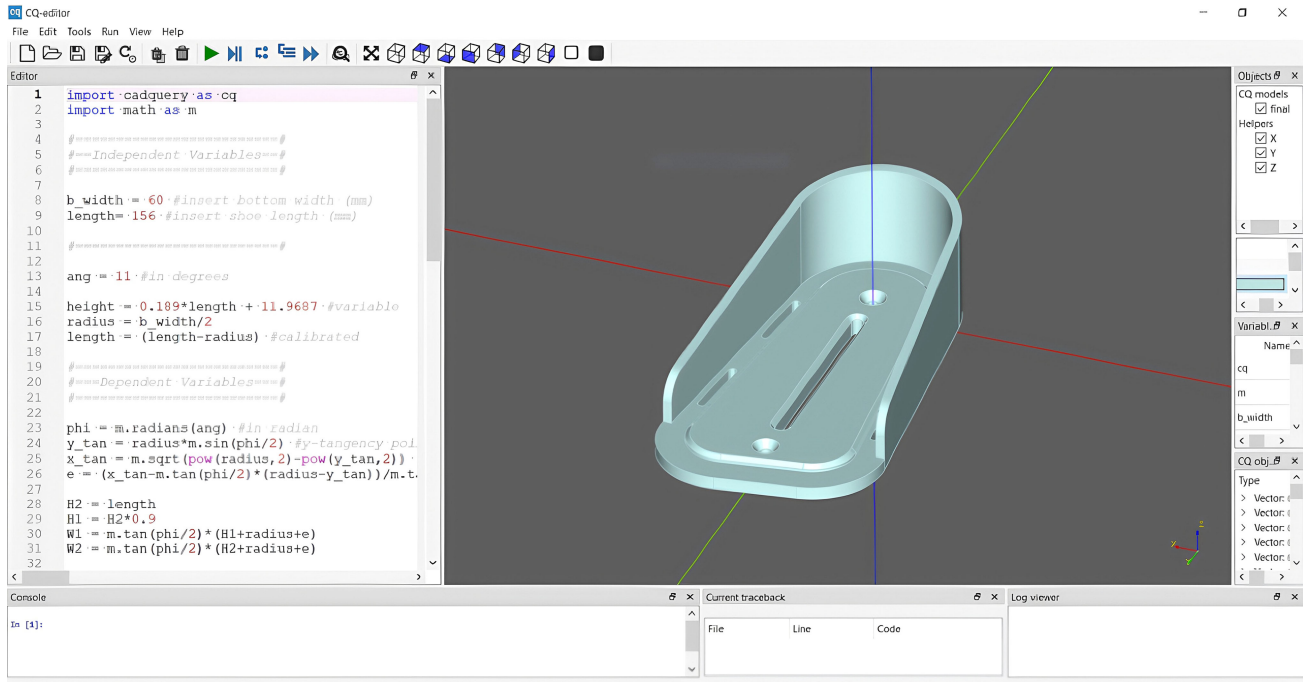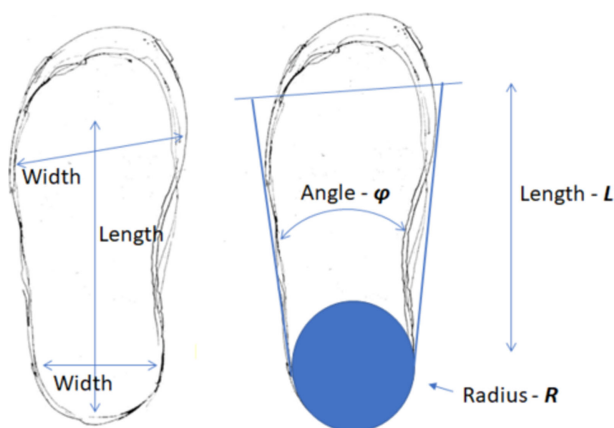

Figure 5
Principle dimensions and independent design variables extracted by the patient's anthropometry. These measurements are needed for the design of the footrest

- The top width extraction (Figure 10) crops the contours of the show using a minimum area rectangle. It then crops the top 30% of the resulting contour and then evaluated its width. This method has proven to be highly effective in that the estimations and the true labels correlated heavily.
- Bottom width extractor (Figure 11) is the more complicated algorithm of the three; it draws a minimum area triangle around the shoe, which due to the shape of the shoe will always have a vertex underneath the shoe and two toward the upper parts. Due to the orientation of the triangle, two of its

edges will intersect with the circle forming the back part of the shoe. We draw a straight line from the lowest most point in the contour as a line that passed through there must necessarily form a constant function. Every three lines can form a circle, so we use the information we have about the three lines and evaluate the value of the diameter of the circle formed between them above the constant line. This diameter appears to correlate with the measured bottom width labels. The following graph depicts the process under consideration.

4.3. Deep learning for the footrest design support

The extracted values of the computer vision algorithm can have some constant imbedded biases. The algorithm could always overestimate or underestimate certain values.

To deal with this, the value estimations of the computer vision algorithm are fed into a ML algorithm, which rectifies any error or bias shown by the computer vision component. The ML algorithm constitutes a simple multilayer perceptron with 1 hidden layer of size 2 nodes. We elected to use a smaller model due to training data size constraints. Every dimension has its own trained model, meaning that three models are trained for the length, the top width, and the bottom width, respectively.

Note that we used Adam optimizer [19] and we found that a learning rate of 0.01 works well with our limited data.

5. Experiments

5.1. Data overview

The data that have been used in this work are labeled training data composed of the A4 sheet scan or image in accordance with the image taking guide – said guide can be found in the appendix.

Figure 6
The Web 3D Modeling component can be accessed through the web. The interconnections with the core components have been put in place and the tool can be used to provide manufacturable models of the footrest component
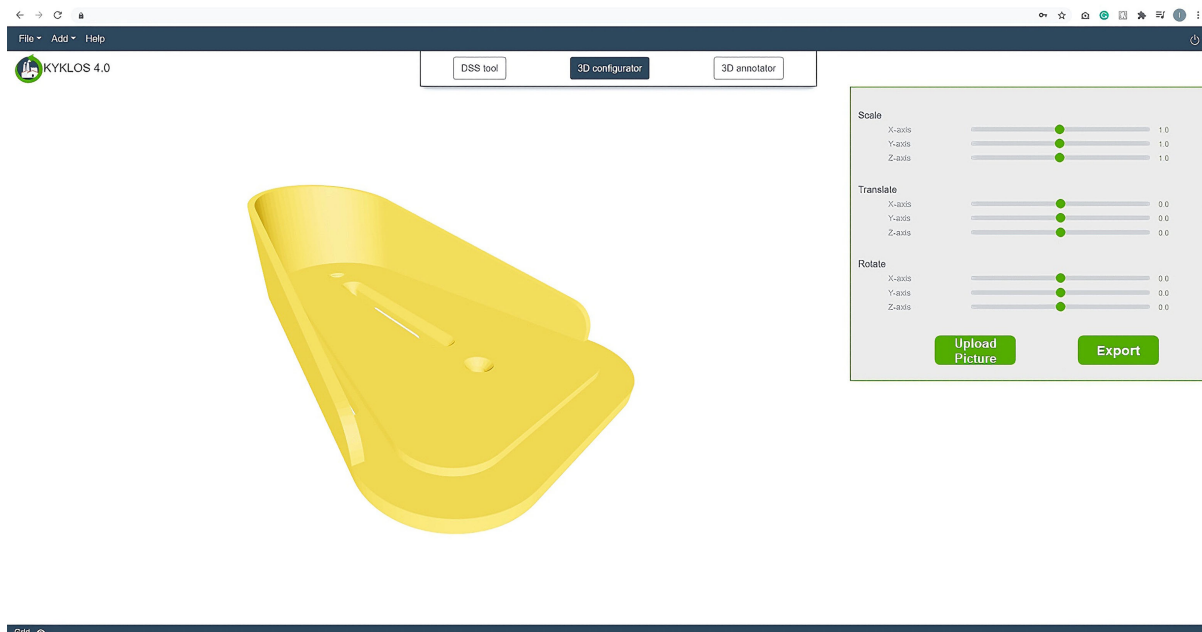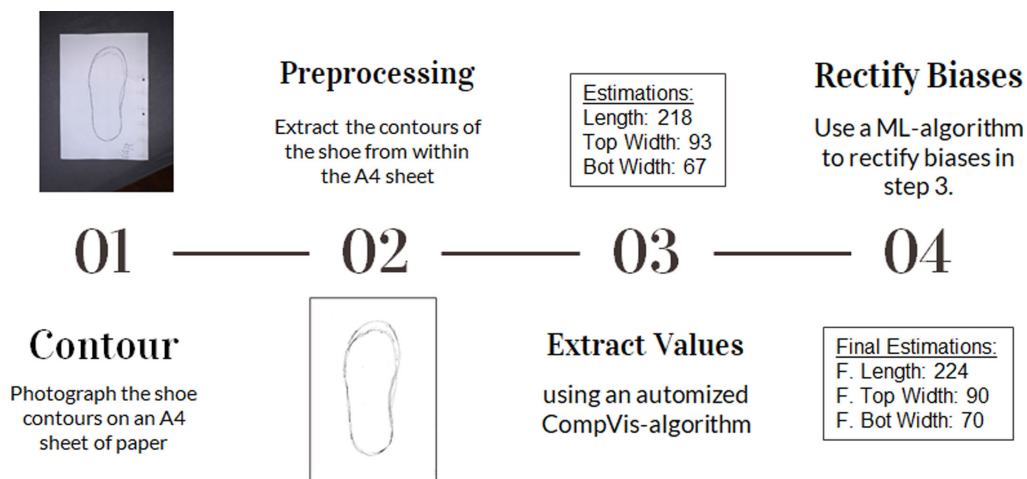

Figure 7
Footrest design customization implementation. This figure shows how computer vision and machine learning are combined to extract the anthropometric measurements

The data include the hand-made measurements of the shoe, which are only used during training, as the actual use case involves streamlining the dimension measurement by outsourcing it to the algorithm. Shoe samples collected so far have the following features.

5.2. Data structure

The raw data are composed of an images folder that contains all the images stored whose title is best described using the following regular expression:

[0–9]{3}_[ft].jpg

Example figure that shows an example raw images directory. The letters f and t at the end of the name refer to true and false as an answer to the question of whether the image constitutes a scan or a photographed image of an A4 sheet of paper.

The labels are stored in a numpy file, which contains a single numpy array with the shape nX3, where n is the number of traces.

5.3. Data collection procedure

This section simply gives an overview of how the data (mainly pictures) are being collected in the promedicare use case.

Figure 8
Shoe's contour detection. Examples of shoes' contours used in the footrest design
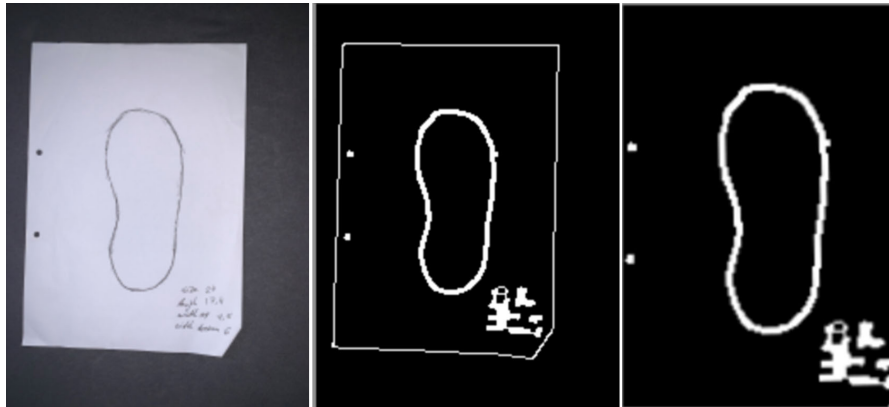
Figure 9
Shoe length extraction

Figure 10
Top width extraction

5.3.1. Basic idea
Taking shoe image

- Place the shoe in the center of the A4 sheet
- Trace the outline of the shoe around the sheet with a pen/marker
- Take an image of the outline or scan it

Measure actual shoe dimensions

Motivations: Only relying on the picture can make our software overestimate the actual shoe sizes. So it is very helpful to measure the actual shoe dimensions by hand.
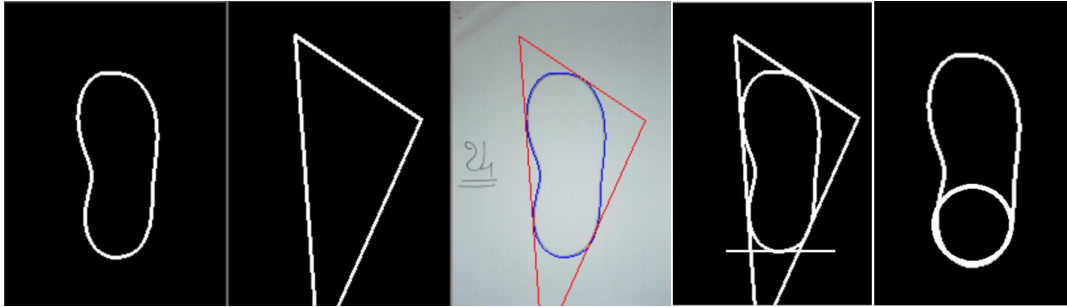
- Needed measurements: The top width, the bottom width, and the length as shown in Figure 5.

5.3.2. Aspects to take into account when taking the picture

1. ***Blank non-white Background:*** If you do not send a scan, please make sure that the background has no visible patterns. Also make sure that there is a visible contrast between the background and the the sheet of paper (please do not place sheet on a white background)
2. ***No folds:*** Please make sure that the A4 sheet is not folded and is completely visible
3. ***No shadows:*** Images without shadows and ones that are evenly lit are sure to work in the program
4. ***Pens/Marker:*** Use a pen or marker when marking the outline and not a pencil
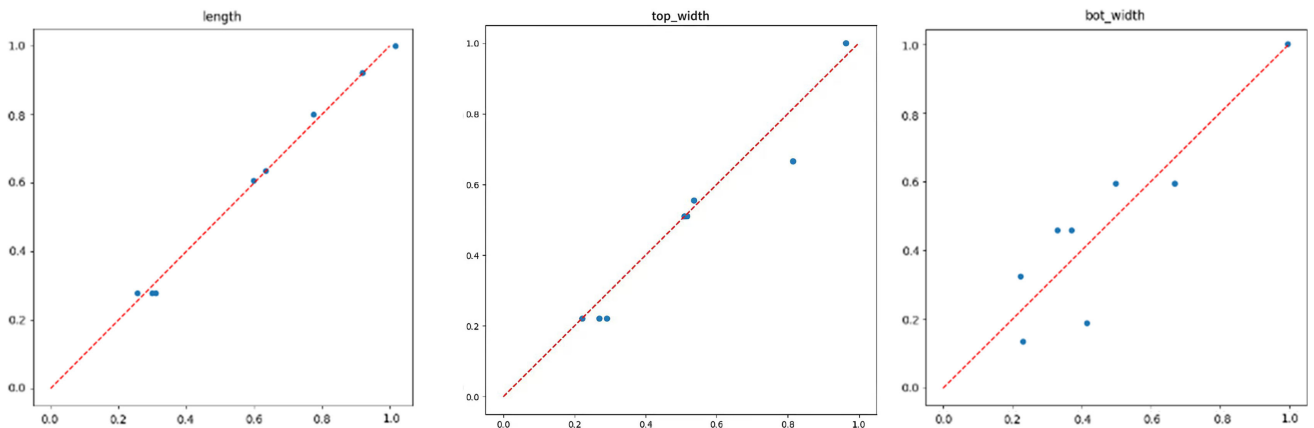
Figure 11
From left to right – Procedure for extracting the shoe bottom width

Figure 12
Samples of shoes' contours used in the experiments

Figure 13
Anthropometric measurements evaluation. (Left) Evaluation results for the Length. (Middle) Evaluation results for the top width.
(Right) Evaluation results for the bottom width

5. *Naming:* We would greatly appreciate it if you titled the image as in the example in millimeters

For example: shoe_180_77_65.png, where the length $= 180$ mm, top width $= 77$ mm, and bottom width $= 65$ mm

Examples:
Here are good and bad example of images we have received or taken so far.

5.4. Performance

Here are graphs showing the performance of the computer vision component (Figure 13). Due to the small size of samples ($N = 24$) that were collected (Table 2, Figure 12), the ML component showed negligible advantage over the pre-processed data. The values were scaled using a Min Max Scaler [20], a transform that scales each feature to the range between 0 and 1, where the minimal number is mapped to 0 and maximum value to 1.

The length shows a very tight correlation, which indicates that our length estimation heuristic was very accurate when used with our training data. The same can be said to a lesser extent regarding the top width estimations and even less so about the bottom width estimations. We did however see a high correlation between the bottom width of the other values, which indicates that the other values can with enough training contribute to the estimation of the bottom width.

Another thing to consider is the fact that we refrained from utilizing the contours in our training, this is mainly due to training data size constraints. With enough data, a ML algorithm would have no need for the shoe dimension estimations and would be able to evaluate the shoe dimensions only using the contours and the pixel density (the pixels per metric discussed earlier in this section).

It is important to note that we do not extract shoe European size, but real shape of used shoe, in order to avoid problem related to shoe type or gender. It should also be noted that some patients also have custom shoe and made. The final footrest will perfectly fit with actual real used shoe.

Regarding the height of shoes, the method we followed to validate the algorithm used a statistical measurement of the heel of different kinds of shoes (both adults and kids) and a correlation between the height and the length was established as a first polynomial regression with a satisfactory root-mean-square-error.

6. Declarations

This work has been undertaken in the context of the European H2020 project KYKLOS 4.0 [21].

The authors have no relevant financial or non-financial interests to disclose.

All authors contributed to the conception and design of the solution as well as the paper writing. The wheelchair design was undertaken by Luca Rizzi and Ilias Zournatzis. The specifications of the computer vision and machine learning parts were provided by Yacine Rebahi and Mahmoud Gharra. The implementation of the algorithms was done by Mahmoud Gharra. All authors read and approved the final manuscript.

In the context of the Kyklos 4.0 project, some data related to the shoes' contours was collected in order to be used for the implementation and validation of the deep learning algorithm. This data will be made available from the corresponding author (Yacine Rebahi) on request. However, the implementation code will not be made available.

On behalf of all authors, the corresponding author states that the conducted research does not involve human participants and animals.

7. Conclusion and Future Work

The main goal of this work is to simplify the entire workflow of wheelchair footrests production and customization.

This paper started by discussing how AM and 3D printing can be a key factor in optimizing the design and production of wheelchairs. It also presented the tangible benefits that this approach brings especially when combined with AI and ML techniques. After having given an overall architecture of the solution, the focus was more on the design of the footrest component and the use of deep learning techniques and computer vision to generate appropriate anthropometric measurements. The solution was also validated through experiments based on real data. Although the amount of data used in the experiments is small, the obtained results are promising and will be improved in the near future by considering larger datasets.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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