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Industrial AI in Manufacturing

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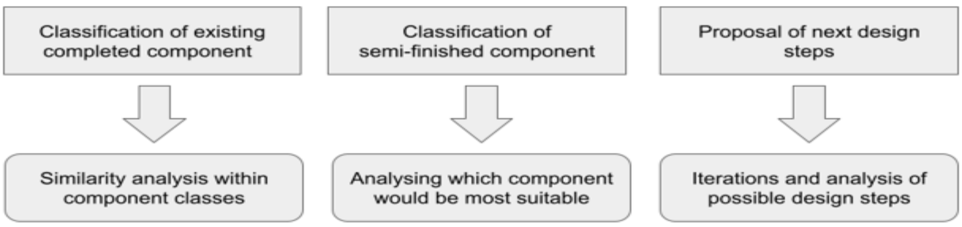
Abstract:- Engineering expertise and the digitization of all business operations are the important factors in today's industrial firms' success. The engineer's design process and expertise are highly personal, and rule-based procedure explanations are almost always difficult and/or time-consuming. As a result, passing on existing information to new engineers, particularly training effort, is very challenging. Another issue is the lack of an overview of the company's existing components. Multiple designs and engineers spend their valuable time as a result of this. The goal of this approach is to use machine learning techniques to extract information from current CAD models and codify it. Furthermore, proper categorization and similarity analysis should reveal existing components rapidly.For this, an AI-based support system will be developed. Engineers merely need to adjust the parameters of the proposed components based on the application. The assistant should then be able to recommend an appropriate next design step based on the existing CAD data and design history. As a result, current CAD models' implicit empirical knowledge supports production-friendly design and the avoidance of design errors.

I. INTRODUCTION

The level of innovation in an organisation determines its success.

- This entails product and service innovation as well as internal value stream design for each market offering. As a result, an industrial firm's primary competences are product creation and manufacturing procedures. Relevant efforts are being made to improve production and logistical systems, as well as internal organisational processes, through digitalization. Individual product design knowledge, individual ties to product characteristics, and historical knowledge of similar product generations, in particular, hold a lot of promise for improving the product development and the design process.
- Transparency: This article discusses methods for achieving the needed transparency, as well as automated design possibilities based on individual preferences and previous product generations. An AI-based approach is a must because of the goal of transferring large inconsistent datasets and such support systems to different product categories.

II. STATE OF THE ART



Here we see the development steps of the approach.
The existing database is categorized to enable the designer to find the most suitable part for his purpose. In a next step, components currently in process are classified in order to propose already existing, similar components to the designer. In the last step, the explicit next x design steps are suggested, which are then on the order of case-by-case are measured on the assigned parameters. Component class instance includes lid, housing, process connectors etc.

Fig. 1

Because it is not strictly defined according to predefined standards, the design process is very individualised and empirical. This frequently necessitates tacit and unformalized experience. A non-automated system model for product feature ideas based on product-generated data is another option. The current AI-based CAD model processing approach focuses more on categorization problems. The degree of automation can be used to distinguish these approaches. On the one hand, it encodes specific model features using hand-crafted descriptors and processes them using machine learning techniques. A CAD model, for example, is grouped initially using the kmeans technique. These clusters can then be used for classification in the second stage.

On the other hand, there is a method that can learn the traits to consider automatically from the incoming data. The multi-view method generates 3D photos components from many angles. For image processing, standard CNNs are used to classify the images. The main idea is to forecast the class based on the angle of view used to make the image. It is based on the object's approximation through the cubic lattice. A 3D convolution kernel categorises CNN-generated voxel structures, just like pixels. The coordinates of randomly distributed points in the volume or on the surface of the model are used as input to the CNN in the

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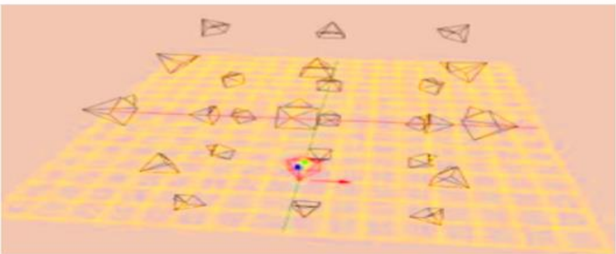
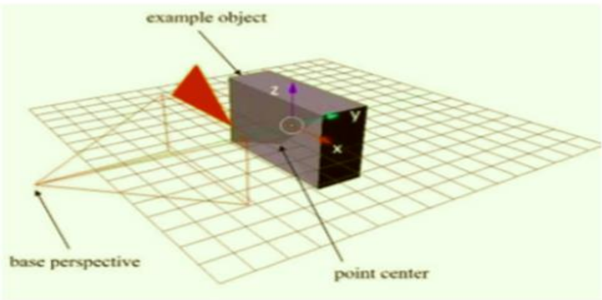
point cloud-based technique.The classification result should be unaffected by the sequence in which the points are entered. An edge-constrained convolution technique is other option. Specific signals are allocated to vertices in this method based on adjacent vertices and input edges. The convolutional layer's local characteristics are detected by clustering points or vertices that are spatially adjacent to one other, both in a point cloud and a graph-based approach. There are several techniques of comparing 3D model similarities. Feature vectors are the most frequently utilised method. The distance between the vectors determines the similarity of the 3D model described by these vectors. The actual design process and implementation, on the other hand, is left to the designer and his expertise. Therefore, this paper develops a way to formalize existing knowledge to pass it on to inexperienced designers and to use it to support repetitive activities not requiring creativity

III. METHODOLOGY



Alignment of the 26 perspectives regarding the basis (red)

Fig. 2

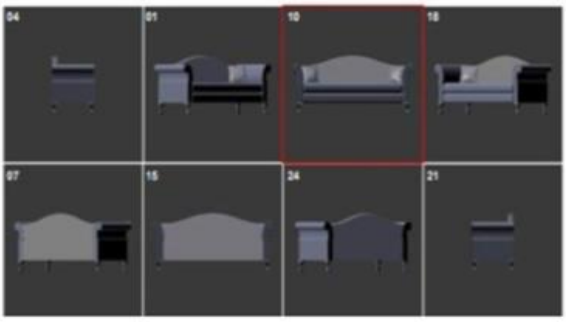


Alignment by standard orientation

Fig. 3

As shown in Figure 1, the examined design aid can be divided into three development stages of increasing complexity. The method is first applied to individual components, which are referred to as components in the following. The goal is to apply the method to assemblies as well. Individual components are represented by 3D CAD models, which serve as the foundation for the developed approach's input and output. A classification of the different product groups is required in order to locate already existing, highly comparable CAD models in a company's data base. Following that, semi-finished component classification must be developed in order to offer relevant, previously existing CAD models to the designer during the design process based on the design phases already completed. On the one hand, the appropriate category must be anticipated, and on the other, the class's most likely related component(s) must be provided. It is now no more an issue of complete pieces in the last stages of development, but of appropriate future design steps. The goal is to make the approach as clear as possible to the designer, including the adaption of case-specific parameters to the respective design steps.

A. Considered database and information content:



Sample perspectives of object

Fig. 4

Understanding the 3D data and how it can be stored is necessary for applying machine learning to 3D models. There are two main formats here: boundary representation (B-Rep), which stores the body's surfaces, and constructive solid geometry (CSG), which stores the body as a collection of basic bodies (e.g., cuboids, cylinders). Internally, most commercial CAD software uses a CSG-based storage format. Individual steps taken by a user to design a basic body are recorded, including parameterized dimensions. The parameterization allows for changes to the fundamental body to be made afterwards. The so-called PART (.prt) format, which is used in the approach proposed in this work, is a very frequently used format.This file format provides information on the design process, which is represented in the so-called structure tree, in addition to geometric information (also model tree or element tree). It contains the individual design steps, sometimes known as features (such as drilling), as well as the parameterization for each (e.g., diameter of the drilling). The structure tree can be used to extract and codify the technique of expert designers when designing pieces of a specific class from already existing CAD models. The structural tree can be read out in the form of an XML file, for example. B-Rep formats, on the other hand, are designed for file exchange between different CAD systems, but information about the design process is lost during conversion. From this file format, information regarding only shape can be extracted.

B. Classification of components:

Because existing CAD models in a company are frequently kept in an unstructured state, they must first be assigned to component classes. The categorization was done within the scope of this project using the Multiview approach, which is only based on shape information. The smallest bounding box of the 3D objects is used to determine the standard orientation. The concept to note here is that objects of the same class have identical length,

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width, and height proportions. A standard orientation can be found by rotating and displacing the smallest bounding box according to some specified rules.Following that, virtual cameras can generate the corresponding photos of the 3D object from the defined views. The standard orientation is defined by five criteria:

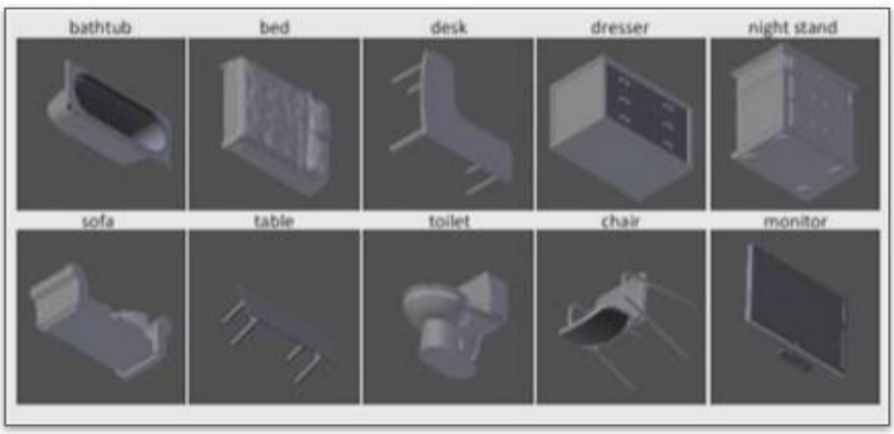
- The centre of the bounding box lies in the origin of the coordinate system,
- the basic perspective shows the largest side surface of the box,
- the longest side of the box is parallel to the x-axis, the point centre of the polygon mesh representing the 3D object has a
- yvalue and a
- zvalue less than or equal to 0.

A sofa is represented in Fig. 4 with photographs of the base perspective (framed in red) and the seven additional perspectives all positioned in the same plane. Finally, these images are fed into CNNs that are viewpoint specific. The images of two opposing perspectives are summed for this purpose, resulting in only 13 CNNs for the 26 perspectives. The input data is then classified by each CNN based on the two picture views. The probabilities for each perspective specific CNN are added together for the final classification of the item, and the object is allocated to the class which has the highest probability.During the design phase, classification of semifinished components is required in order to offer to the design engineer equivalent existing, very similar parts. A semifinished part is one that is currently being manufactured. From the current state of the design process, numerous classes may be appropriate. The more complex your design is, the easier it will be components categorization. This classification is accomplished in the developed approach by training the current approach in other semi-finished items. A CAD model's intermediate status is usually not saved separately in the company's database and must be produced intentionally.To achieve this, either remove the structure tree's features one by one or save the CAD model's intermediate status. The design assistant may see what type of part the designer is designing, search for very similar parts in the existing CAD model, and communicate with the designer by being able to categorise semi-finished pieces as the designer works. To whom the first draught of completed parts is provided. Make case-specific adjustments as needed.

C. Proposal of next design steps:

You must first classify the semi-finished items to ascertain what type of component is there before proposing the next explicit design step. After you've defined the component class, you can use the design process to suggest the next design step. The structure tree is extracted from all existing CAD models of the appropriate class to understand the steps specific to this component class. Appropriate ML methods (such as Random Forest) are trained to uncover common design trends using these structure trees. The construction assistant's job is to present a variety of options. It also indicates the likelihood that the assistant will accept the recommendation in order to maintain adequate traceability.By simply suggesting the next step, the designer can make adjustments as soon as needed. Finally, the next proposed procedure is based on these adjustments.

IV. CASE STUDY



3D models of 10 different categories from ModelNet10
fig 5

Fig. 5

Figure 5 shows the ModelNet10 database, which has 4899 3D models of various furniture in ten different categories. As a result, the classification process entails categorising models into ten separate groups. First, only one perspective photos were used to evaluate the three distinct CNN architectures. One architecture is based on the Alex Net architecture, another is based on the modified VGG-16 network, and the third is a custom configuration. The self-developed architecture is shown in Figure 6. The names and parameters of the layers are contained in the rounded rectangles; for example, the first convolutional layer uses 32 kernels of size 3x3 and the Rectified Linear Unit (ReLU) as an activation function.The input and output formats of the layers are indicated by the names on the

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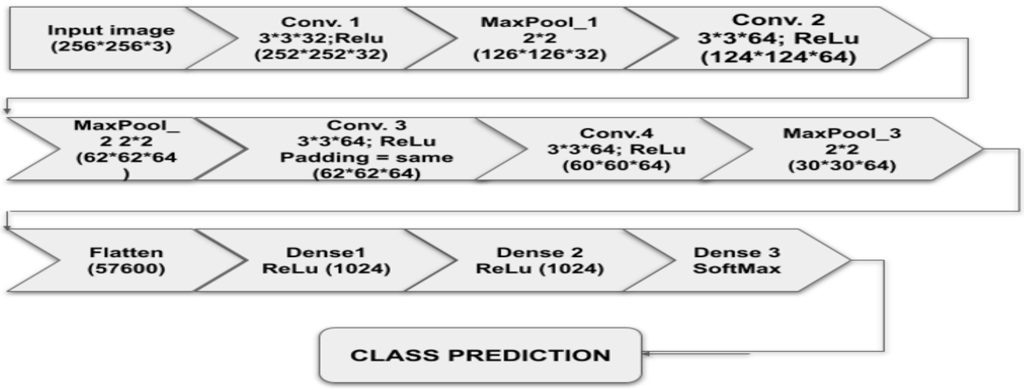
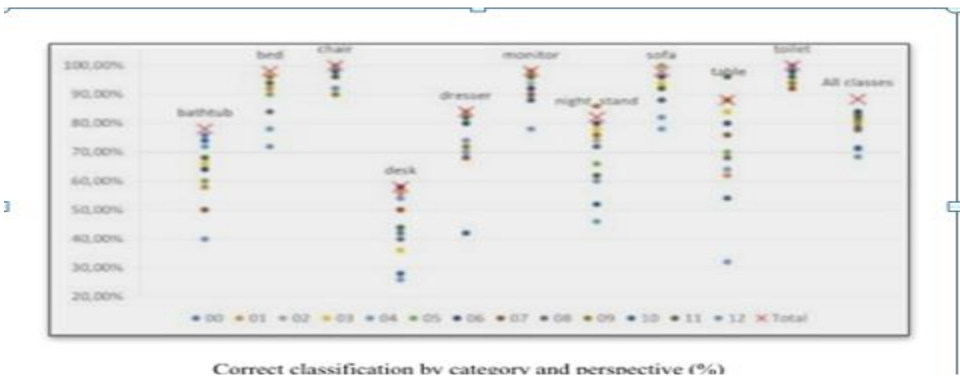
arrows, for example, the input picture is 256x256 pixels with three channels. Despite the high number of factors, the performance of the displayed architecture is betterthan the other two, which is why the results for this architecture are presented. The accuracy of the look at information is 80.0 percent when snap photos are taken from a single perspective. One reason for the latter architectures' worse overall performance is that they were meant to differentiate a somewhat wider range of learning.



Architecture of CNN

Fig. 6

The self-advanced structure became widely used for all different viewpoint-precise CNNs as a result of the effects received for snap photos from a single perspective. As shown in Fig. 6, each of those CNNs was configured. Depending on the perspective, the accuracy of man or woman views ranged between 68.4 percent and 84.0 percent. A final check accuracy of 88.4 percent was achieved by merging the individual projections and averaging over all perspective-precise magnificence predictions. The accuracy of the man or woman views, as well as the overall accuracy after taking all views into account (crimson x), are displayed for each item.The general impacts for all views are shown in Fig. 8 as a confusion matrix. For instance, most effective 58 percent of desks are correctly classified as such, but a large minority are misclassified as sofas. One reason for this is because items from distinct lessons appear to be extremely similar from certain perspectives (e.g., the rectangular base of a settee or desk). As a result, it becomes clear that analysing the items' field of vision alone may not be adequate; their shape should also be considered. Graph-primarily based approaches can be appropriate for this, and they should be considered in comparable projects.The objective is to base the category on actual CAD data from a business dimension generating provider that is available in PART format. Following that, the form tree is extracted from those CAD fashions, and the layout assistant's actions are followed.



Correct classification by category and perspective (%)

Fig. 7

V. CONCLUSION AND OUTLOOK

Based on appropriate machine learning approaches, this research presents a three-step methodology for a CAD design assistance. The support system can only classify components in the form of 3D CAD models which are in the early stages of development. For this goal, an original method is described that translates 3D models into a standard orientation before generating 2D photos from diverse views.As shown in a case study, those perspective-specific images are finally used as input for CNN classification. Additional CNN architectures should be examined in future study, especially those having fewer parameters. Other approaches, such as graph-based approaches, should also be investigated to better map the component's structural architecture. The classification of semi-finished components is examined in the approach's next development step, so that existing, very similar components can be proposed to the designer during the design process. Using appropriate machine learning methods, a general approach or design pattern for each

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class is learned from the design history stored in the CAD models in the final development step.

	bathtub	bed	chair	desk	dresser	monitor	night stand	sofa	table	toilet
bathtub	78	0	0	0	0	0	0	0	0	0
bed	8	98	0	2	0	2	0	2	0	0
chair	0	0	100	8	0	0	0	0	0	0
desk	2	0	0	58	2	0	0	0	12	0
dresser	0	0	0	2	84	0	16	0	0	0
monitor	2	2	0	0	0	98	0	0	0	0
night stand	2	0	0	4	10	0	82	0	0	0
sofa	8	0	0	18	2	0	0	98	0	0
table	0	0	0	16	0	0	2	0	88	0
toilet	0	0	0	2	2	0	0	0	9	100

Confusion matrix with actual classes*predicted classes. The proportion per class identified correctly is displayed

Fig. 8

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