https://doi.org/10.24867/GRID-2024-p44 Original scientific paper

CAPABILITIES OF AI IN TEXT-TO-3D MODEL GENERATORS FOR MECHANICAL COMPONENTS DESIGN

Iva Šarčević [1], Tomislav Dorić [1], Ana Ivančević [1], Dubravko Banić [1], Petra Buljat [2]
[1] University of Zagreb, Faculty of Graphic Arts, Zagreb, Croatia
[2] University of Zadar, Department of Tourism and Communication Studies, Zadar, Croatia

Abstract: *This paper explores how effectively Artificial Intelligence (AI) can translate text descriptions into accurate and functional 3D models of mechanical components, highlighting both the potential and the current shortcomings of this technology. A functional 3D model implies that it is suitable for 3D printing. Three different AI 3D model generators were selected for this analysis. Text prompts involving gear mechanisms were used as input. Each generated model was assessed on key parameters such as the accurate depiction of gear teeth, the correct alignment and meshing of gears, and the overall structural integrity required for functional gear mechanisms. Additionally, the generated models were verified for any deviations from the expected design standards of mechanical gears. The analysis revealed that none of the selected AI 3D model generators could consistently produce fully functional and technically accurate gear models based on simple text prompts. While the AI generators could produce visually correct models that generally resembled gears, significant shortcomings were observed in their functional and technical accuracy. The generated models often failed to meet the precise geometric and structural requirements necessary for practical application in mechanical systems. Automating the 3D modelling process for mechanical components using AI technology would reduce time and cost. However, further advancements in AI and machine learning are required to enhance the accuracy and reliability of AI-generated 3D models for use in real-world mechanical design and manufacturing.*

Key words: 3D Model Generator, Artificial Intelligence, Text-to-3D Model, Mechanical Components

1. INTRODUCTION

The field of Artificial Intelligence (AI) has seen advancements in recent years, particularly in generative models. AI image generators have demonstrated satisfactory capabilities in creating detailed and imaginative images from text prompts, showing the potential of AI to translate textual descriptions into visual content. These technologies have already made a significant impact on creative industries by automating the generation of high-quality images and visual art (Kang et al., 2023; Noel, 2023).

AI technologies have also extended their capabilities to 3D model generation. AI 3D model generators use artificial intelligence and advanced algorithms to create three-dimensional models based on textual descriptions, images, and even video inputs. It enables the automated production of 3D models from a variety of input sources, which can then be used for applications such as virtual reality, augmenter reality, entertainment, or in robotics and autonomous vehicles (Tsalicoglou et al., 2024).

The market currently features a significant number of AI 3D generators, specializing in different applications. These tools offer a wide range of functionalities, including real-time full-body motion capture, applications in gaming and architecture, artistic video creation, while others excel in full-body marker tracking or texture generation, as well as capturing high-quality geometry. Each of these generators has its own strengths made up for specific needs in design and visualization (Unite AI, 2024).

In mechanical design, creating and manufacturing components can be both costly and time-consuming. To address this challenge, AI 3D generators have been explored as a potential solution for automating the design process.

This paper investigates the effectiveness of current AI technologies in translating text prompts into accurate and functional 3D models of mechanical components, with a specific focus on spur gear. The aim is to determine if these generators can provide an accurate and viable model, assessing their effectiveness in reducing the time and expense associated with traditional mechanical design and production processes, while also identifying any limitations in their current capabilities.

Three different AI 3D model generators were evaluated based on their ability to produce models that adhere to key mechanical design standards. These standards include the accurate representation of gear teeth, proper alignment and meshing of gears, and overall structural integrity necessary for practical use.

The research shows the need for further advancements in AI and machine learning to enhance the accuracy and reliability of AI-generated 3D models.

2. METHODS

Mechanical components, such as gears, are fundamental elements in a wide range of machinery and devices. The design of these components requires precise specifications to ensure functionality and compatibility within mechanical systems. Traditionally, the design process involves detailed manual drafting and modelling, which can be time-consuming and prone to human error. The integration of AI in generating 3D models from text descriptions offers an innovative solution to streamline this process (Obsieger, 2003).
Three different AI 3D generators were used to create 3D models from a text prompt: Luma AI (Lumalabs, 2024), Meshy AI (Meshy AI, 2024), and Rodin AI (Hyperhuman, 2024). These generators were selected based on their availability and the variety of features they offer for different applications. Each of the generators was tasked with interpreting the same prompt to ensure consistency in the testing process.
The key elements required to define gears include the number of teeth, module, pitch diameter, pressure angle, gear ratio, gear width and gear type. These parameters collectively determine the shape, size, and functional characteristics of the gear within a mechanical system. In this study, the text prompt used for generating the 3D model was as follows: "spur gear: 30 teeth, module 2 mm, 60 mm pitch diameter, 20° pressure angle, 10 mm gear width".

3. RESULTS

Text prompt "spur gear: 30 teeth, module 2 mm, 60 mm pitch diameter, 20° pressure angle, 10 mm gear width" was used to represent a standard mechanical component, ensuring that the AI generators were challenged with producing a technically accurate and functional model.

3.1 3D generator Luma AI

The generation time for 3D generator Luma AI was three minutes. The text prompt resulted in a model of an individual gear, featuring a random number of teeth, arbitrary dimensions, tooth angles, and hole diameter. However, the resulting 3D model is not adequately shaped; it exhibits uneven characteristics, gaps between the teeth, and the hole is misaligned. Despite these issues, the topology of the model; with the "Low" (Figure 1) and "Med" (Figure 2) options selected; remains relatively neat and organized. Tooth alignment between two gears is shown in Figure 3.

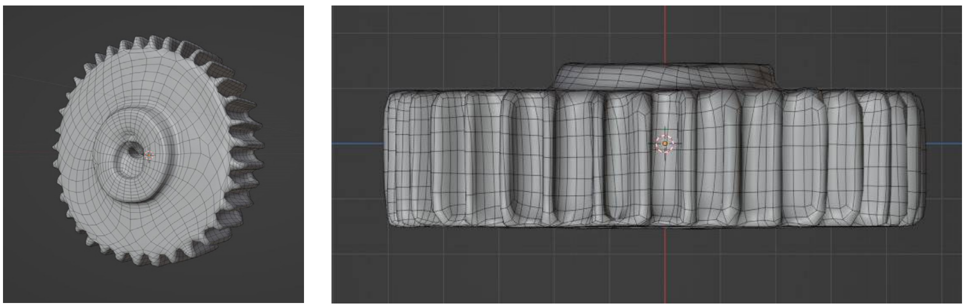

Figure 1: Luma AI model - Topology Display (lower polygon resolution – 5,000 polygons)

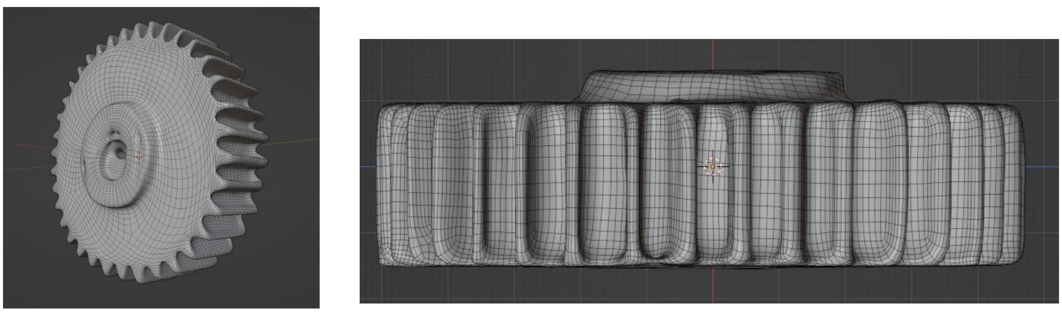

Figure 2: Luma AI model - Topology Display (medium-density polygon resolution – 20,000 polygons)

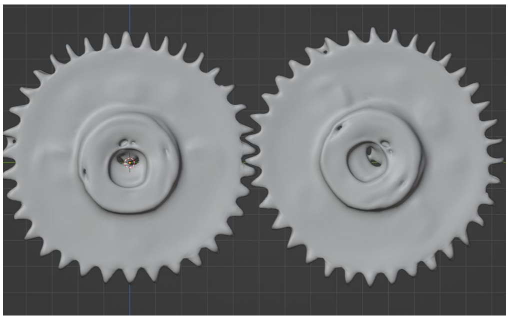

Figure 3: Luma AI model - tooth alignment between two gears

3.2 3D generator Meshy AI

The generation time for 3D generator Meshy AI was one minute. The text prompt yielded several variations of 3D models of different gears. Although these models still featured random parameters and dimensions, they exhibited a correct and adequate appearance, with consistent dimensions, uniform spacing between the teeth, and centered holes with minimal noticeable deviations in geometry. Two out of the four variations were selected for their accuracy, as they displayed no significant irregularities or geometric artifacts (Figure 4).

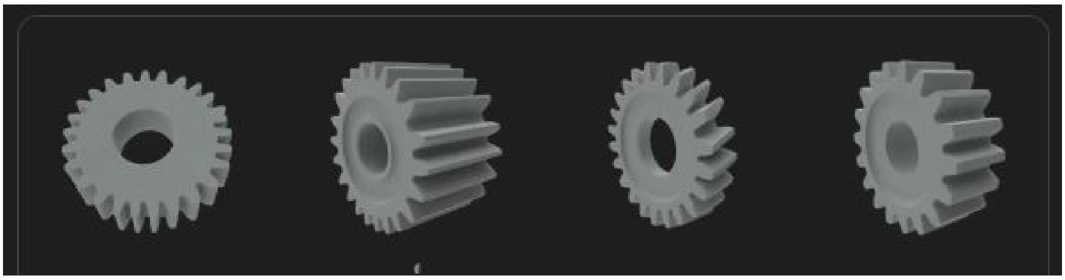

Figure 4: Meshy AI generated 3D models

The first selected variation is an individual gear with random dimensions and a variable number of teeth, exhibiting a slanted horizontal angle. It turned out to be quite accurate, with only minor geometric irregularities (Figure 5). Tooth alignment between two gears is visualized in Figure 6.

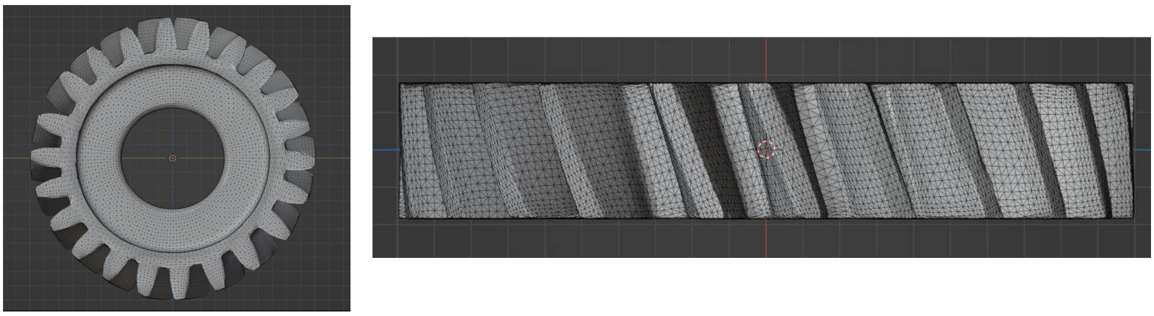

Figure 5: Meshy AI model - Topology Display for the first gear variation

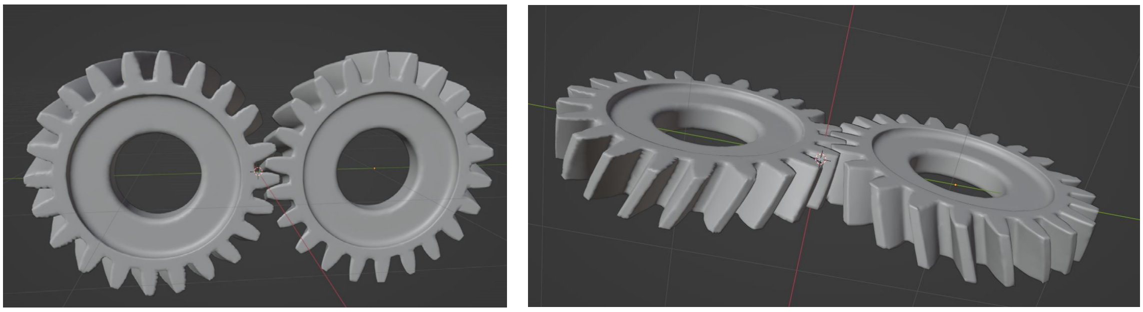

Figure 6: Meshy AI first model - tooth alignment between two gears

The second selected variation is also an individual gear with random dimensions and a variable number of teeth, but it features a correct and uniform shape with straight teeth, equal spacing, and a centered hole, again displaying only minor geometric irregularities (Figure 7). In Figure 8 tooth alignment between two gears can be seen.

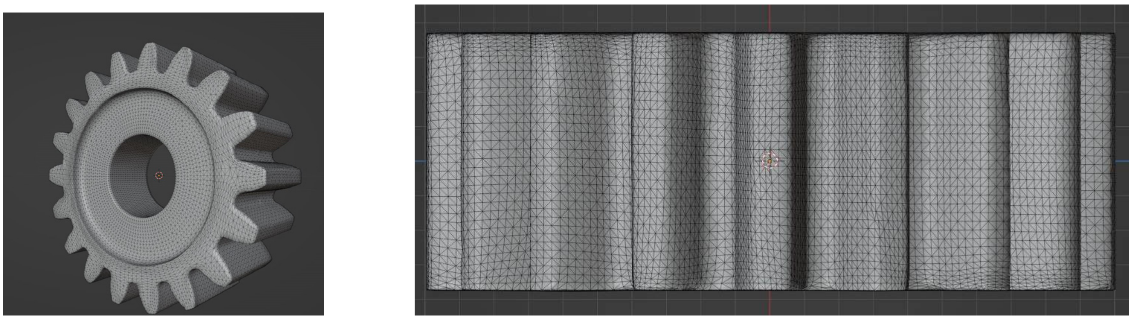

Figure 7: Meshy AI model - Topology Display for the second gear variation

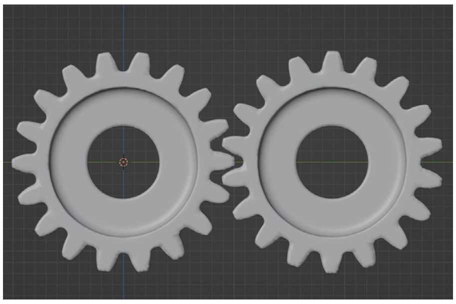

Figure 8: Meshy AI second model - tooth alignment between two gears

3.3 3D generator Rodin AI (Gen-1)

The generation time for 3D Rodin AI was less than a minute. By inputting the textual prompt, a single gear with random dimensions and parameters was generated. It exhibits a correct round shape and a centered hole; however, it features irregular and uneven teeth of varying sizes and spacing. The topology is neat and moderately dense, consisting of 10,000 polygons, although the geometry of the teeth remains irregular (Figure 9). Visualization of tooth alignment between two gears can be seen in Figure 10.

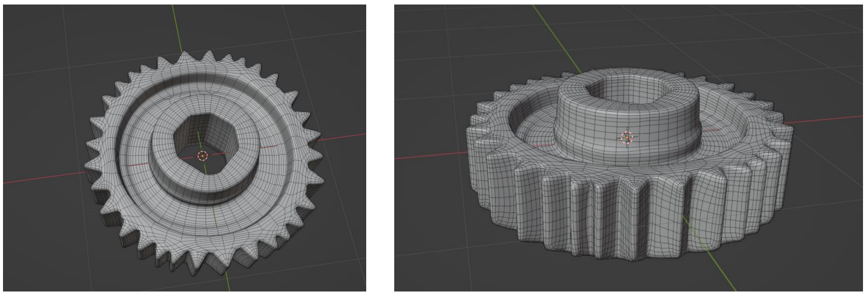

Figure 9: Rodin AI model - Topology Display (10,000 polygons)

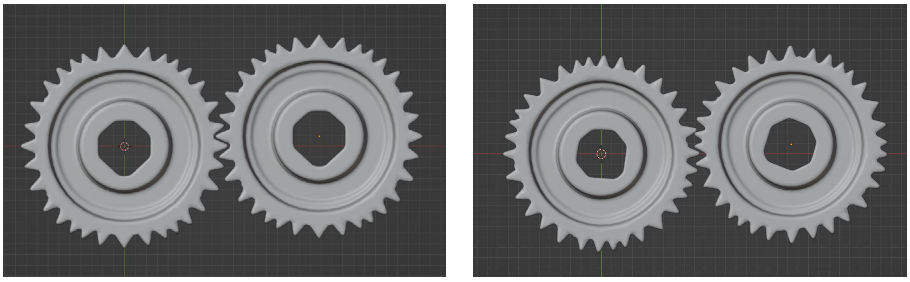

Figure 10: Rodin AI model - tooth alignment between two gears

4. DISCUSSION

The evaluation of three AI 3D generators—Luma AI, Meshy AI, and Rodin AI—provides capabilities and limitations of these technologies in producing functional 3D models of mechanical components from text prompts. Model generated form 3D generator Luma AI is unsuitable for any real and practical use such as 3D printing, meaningful simulation, or 3D animation. However, the polygons create irregular tooth shapes, which limits the model to only potential digital use where precision is not critical. The 3D generator Meshy AI produced four variations, of which two were selected. The first selected variation is relatively adequate in shape for use in a real mechanism or prototype (3D printing). Its topology is neat and moderately dense, consisting of 50,000 polygons, making it suitable for simple 3D models where high resolution is not necessary; however, this density may represent an excess in terms of system optimization or computer performance. The second selected variation is also relatively adequate in shape for use in a real mechanism or prototype (3D printing). Its topology is neat and denser, similar to the previous example, with approximately 50,000 polygons. The 3D generator Rodin AI produced a gear model that is neither adequately shaped nor suitable for practical use in a mechanism or prototype (3D printing). Each AI 3D generator exhibited strengths and weaknesses. These findings underscore the progress made in AI 3D modelling while also highlighting the need for further advancements to enhance the precision and reliability of AI-generated models for mechanical applications.

5. CONCLUSIONS

In examining the capabilities of three different AI 3D model generators: Luma AI, Meshy AI, and Rodin AI; it becomes evident that these generators exhibit both potential and limitations in generating functional mechanical components from text prompts. While Luma AI and Rodin AI failed to deliver models suitable for practical applications such as 3D printing or simulation due to issues with precision and geometry, Meshy AI showed promise by generating two viable variations. Though not perfect, these models demonstrated an adequate shape and topology for prototyping and basic mechanical use. However, the high polygon count in Meshy AI's models could present challenges in terms of optimization and performance in certain cases. Overall, while these AI tools showcase notable advancements in automated 3D modeling, they still require improvements in precision and usability to meet the demands of real-world mechanical applications. Further development will be needed to improve the practicality of these tools for engineering and design applications.

6. REFERENCES

Hyperhuman. (2024) *Rodin*. Available from: https://hyperhuman.deemos.com/rodin https://lumalabs.ai/dream-machine [Accessed 10th July 2024].

Lumalabs. (2024) *Dream Machine*. Available from: https://lumalabs.ai/dream-machine [Accessed 4th July 2024].

Kang, M., Zhu, J-Y., Zhang, R., Park, J., Shechtman, E., Paris, S. & Park, T. (2023) Scaling Up GANs for Text-to-Image Synthesis. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR, 18 - 22 June 2023, Vancouver, Canada.* pp. 10124-10134. Available from: doi: 10.48550/arXiv.2303.05511

Lüddecke, T. & Ecker, A. (2022) Image Segmentation Using Text and Image Prompts. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 19 - 24 June 2022, New Orleans, Luisiana*. pp. 7086-7096. Available from: doi: 10.1109/CVPR52688.2022.00695

Meshy Ai. (2024) *Creating stunning 3D models with AI*. Available from: https://www.meshy.ai/ [Accessed 5th July 2024].

Noel, G. P. J. C. (2023) Evaluating AI-powered text-to-image generators for anatomical illustration: A comparative study. *Anatomical Science Education.* 17 (5), 979-983. Available from: doi:10.1002/ase.2336

Obsieger, B. (2003) *Prijenosi sa zupčanicima*. Rijeka, Tehnički fakultet Sveučilišta u Rijeci.

Tsalicoglou, C., Manhardt, F., Tonioni, A., Niemeyer, M. & Tombari, F. (2024) TextMesh: Generation of Realistic 3D Meshes from Text Prompts. In*: International Conference on 3D Vision, 3DV 18 - 21 March 2024, Davos, Switzerland*. pp. 1554-1563.

Unite AI. (2024) *Best AI 3D Object Generators*. Available from: https://www.unite.ai/best-ai-3d-object-generators/ [Accessed 8th September 2024].