Czech Technical University in Prague

Faculty of Mechanical Engineering – Department of Designing and Machine Components

Bachelor's Thesis

ARTIFICIAL INTELLIGENCE SUPPORTED MECHANICAL ENGINEERING DESIGN

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Supervisor: Ing. Hadraba Daniel

Study Program: B0715A270024 - Bachelor of Mechanical Engineering

Prague 2024

Declaration

I declare that I prepared my Bachelor’s thesis independently and used only the materials (literature, projects, software, etc.) listed in the reference list.

In Prague ………………… ....

Akiki Charbel

Thanks

I would like to thank the supervisor of my Bachelor's thesis, Ing. Hadraba Daniel, Ph.D. for professional supervision, valuable comments, and consultations for the development of my thesis. A big thank you also goes to my family, who always supported and motivated me throughout the development of this work. Last but not least, I would like to thank me for believing in me.

Akiki Charbel

BACHELOR'S THESIS ASSIGNMENT

I. Personal and study details

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II. Bachelor's thesis details

Bachelor's thesis title in English:

Strojírenské konstruování s podporou umělé inteligence

Bachelor's thesis title in Czech:

Artificial intelligence supported mechanical engineering design

Guidelines:

The individual tasks in the workflow of designing mechanical components and mechanisms today is quite traditional. Of course, the technology enabled designers to complete the tasks faster in larger teams and with higher efficiency, however, the designers still have a full control of every task in the workflow. The current development in AI and usage of generative or optimization tools (3D-GAN, RNN) bring a new possibilities in addressing the designers role. This work should review the current possibilities of AI in traditional mechanical engineering design and provide an example in a case study.

Bibliography / sources:

1) Patel, A.R., Ramaiya, K.K., Bhatia, C.V., Shah, H.N., Bhavsar, S.N. (2021). Artificial Intelligence: Prospect in Mechanical Engineering Field—A Review. In: Kotecha, K., Piuri, V., Shah, H., Patel, R. (eds) Data Science and Intelligent Applications. Lecture Notes on Data Engineering and Communications Technologies, vol 52. Springer, Singapore. https://doi.org/10.1007/978-981-15-4474-3_31
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3) E. Toptas, "Innovative approach to the design of mechanical parts," Journal of Mechatronics and Artificial Intelligence in Engineering. 2020; Vol. 1, No. 1, pp. 14–20. https://doi.org/10.21595/jmai.2020.21473

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Date of bachelor's thesis assignment: **26.10.2023** Deadline for bachelor thesis submission: **19.01.2024**

Assignment valid until: ___________

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III. Assignment receipt

The student acknowledges that the bachelor's thesis is an individual work. The student must produce his thesis without the assistance of others, with the exception of provided consultations. Within the bachelor's thesis, the author must state the names of consultants and include a list of references.

27/10/2023
Date of assignment receipt

Student's signature

Annotation list

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Abstract:

An Investigation on the Integration of Artificial Intelligence with Mechanical Engineering Design: This thesis explores the profound influence of artificial intelligence (AI) and machine learning (ML) on the process of mechanical engineering design. The text conducts a thorough analysis of conventional design approaches, contrasting them with the dynamic, efficient, and innovative possibilities brought about by AI and ML technology. The study emphasizes the significance of datasets, AI algorithms, and their utilization. An important achievement is the creation of 'Engineer's Ally,' a program that utilizes artificial intelligence to aid in mechanical engineering design. This tool showcases the practical implementation of AI in connecting theoretical understanding with practical engineering problems. The thesis also examines crucial factors such as ethical considerations, privacy problems, and the difficulties of incorporating AI into established mechanical engineering systems. The article provides an equitable viewpoint on the capabilities and constraints of AI in mechanical engineering, highlighting the necessity for continuous investigation and ethical supervision in this swiftly progressing domain.

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Introduction

Mechanical design, a fundamental aspect of mechanical engineering, encompasses the conversion of resources and energy into functional mechanical structures and operations, resulting in the creation of machines and equipment that fulfill human requirements. This involves the development or improvement of equipment, a process usually achieved using various software tools, importantly CAx systems that replicate the life cycles of components and machines in a virtual environment. The ability of a mechanical designer to translate ideas into workable, affordable, and feature-rich devices is fundamental to the field. Nevertheless, contemporary technical obstacles are progressively intricate, frequently resulting in design flaws as a result of time limitations, budgetary constraints, or inadequate expertise. Contemporary designers are adopting innovative techniques provided by the fast-advancing world of information technology, instead of relying on outmoded catalogs and procedures.

The integration of artificial intelligence (AI), machine learning, and automation plays a crucial role in this revolution of the design process. These technologies not only accelerate the process of development and decrease expenses, but also greatly limit the occurrence of errors. By utilizing specialized algorithms, they reduce the necessity for considerable human participation in data collecting and analysis.

This study offers an exploration of the capabilities of deep learning and machine learning to transform the design process of mechanical components and assemblies. Machine learning, a fundamental component of artificial intelligence, offers a multitude of possibilities for creativity in the field of mechanical design and optimization. The purpose of this thesis is to identify and analyze these perspectives, demonstrating their potential to contribute to society and advance the field of mechanical engineering. Moreover, mechanical system design integrates scientific, industrial, and social endeavors in a regulated hierarchy, spanning from conceptualization to production. Conventional design processes, frequently assisted by computer-aided design (CAD) software, are impacted by variables such as material composition, mechanical durability, and manufacturing techniques. Nevertheless, the potential of these designs is constrained by the ability of both the designer and the program.

The emergence of AI, namely its subfield machine learning, presents an adaptive process that improves the learning and problem-solving capabilities of computer systems as time progresses. An impressive breakthrough in this field is Generative Design, which utilizes AI to provide creative design solutions according to particular criteria. This methodology facilitates the swift creation of numerous design alternatives within specified parameters, expanding the range of possibilities beyond conventional techniques.

Traditional designing

The design and development of profitable new products is crucial for the financial health of a product development organization. In order to remain competitive in the global market, corporations are compelled to create and innovate new items that not only exhibit enhanced quality, but also undergo quick development, all while minimizing expenses (1). The process that corporations employ to bring new items to fruition and their management of this process are crucial factors in determining the success of the company (2). Simon (3) argues that the tactics utilized in the design process can impact both the efficiency of resource utilization and the characteristics of the final design.

Therefore, the development of design processes is a crucial element in the strategic advancement of goods, ensuring the long-term competitiveness of an organization. The walkthrough of design processes entails the methodical examination and combination of the processes that a corporation employs to create a product (4) (5).

Working with companies in many industries such as medical devices and consumer goods (4), it has been found that determining the appropriate design process is not straightforward, even for relatively simple products. Below are examples of design process evaluations.

1. are designers demanded to collect supplementary information regarding the problem?

2. Is it necessary to further break down the design problem (6)?

3. Should designers choose innovative designs or use existing concepts to meet design requirements?

4. is there a need to find new possibilities in solving or stick to existing ones

5. developing subsystems internally or hand it out to third parties?

These decisions are commonly known as the 'design process-related decisions'. The determinations regarding the progression of the design process are distinct from the determinations concerning the specifications of the product, such as the materials, shapes, dimensions, and so on. The decisions made during the design process have significant implications for the finished product's ability to meet criteria, the time it takes to develop and manufacture the product, and the cost of the product. Moreover, the challenge of determining the sequence of the design process becomes more pronounced as the complexity of the product intensifies. Determining the progression of the design process is challenging due to the inability to fully explain it in advance. The success of downstream activities relies heavily on the information produced by upstream activities, and the level of uncertainty is continually elevated. The challenge that firms encounter when determining the direction of the design process has inspired the development of a computer environment that facilitates systematic analysis and decision-making in design (7). A model that properly depicts the ongoing design process and facilitates the analysis and decision-making process connected to the design is a crucial component in the analysis and decision-making about the progress of the design process. Considering the structure of the design and available options are essential in the making of a “design node”. The technique incorporates two design strategies: top-down and bottom-up.

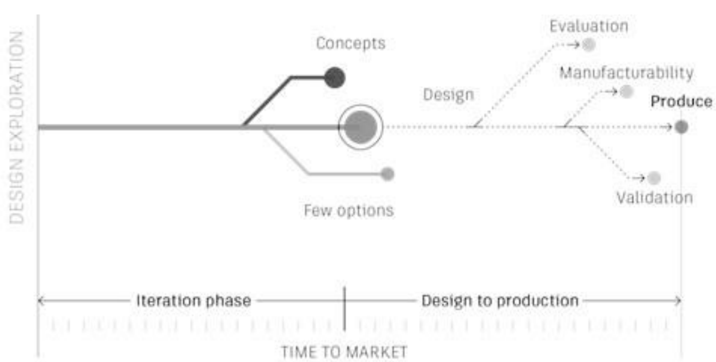

Fig. 1.: the traditional approach process in the design of mechanical parts (8)

Top-down

Figure 1 displays the node for decomposing the top-down design (DR: Design Requirements, DP: Design parameters). Following is the explanation of what problems are encountered while designing and how its systematically analyzed. A top-down approach involves moving from abstract levels to concrete levels and the more specific it becomes the more problematic importantly noting that values of the design parameters become more and more critical throughout the process. Top-down design analysis is defined by the following characteristics:

(a) The design parameters being considered;

(b) The requirements that the design parameters must meet;

(c) The various values that the parameters could have;

(d) The available information or knowledge to inform the design decision.

(e) the predetermined values for the parameters.

It is important to mention that the chosen parameter values do not guarantee the selection of a particular value.

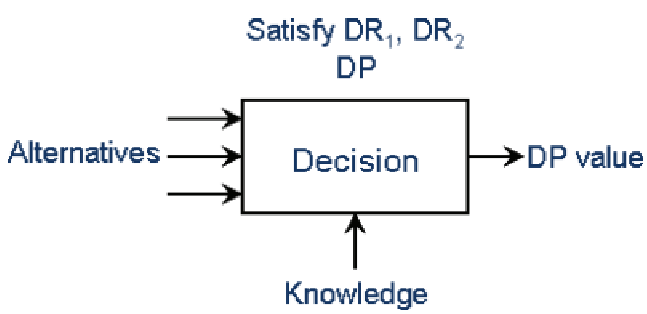

Fig. 2.: Top-Down Design Decomposition

It should be noted that the values of the selected parameters do not suggest that one value was picked for each parameter. The answer to this question depends on the precise requirements that must be met as well as the amount of knowledge or experience that is already available to help with decision-making. For example, a design parameter for choosing the material to be utilized in a product can include options such as composites, metals, ceramics, or plastics (5). The characteristic may also apply to other material classes, such as plastics or ceramics, in addition to these. By removing alternatives, this strategy reduces the vast design possibilities that come with design issues, leading to smaller design regions. This is another example of delayed design decisions.

Bottom-up

The bottom-up design evolution node is shown in Figure 2. The description of the design problem and the design activities completed to generate the design solution are outlined in this statement. The bottom-up technique does not include going from a general level to a particular one, in contrast to the top-down strategy. Using particular solutions to ascertain the values for design parameters is the bottom-up design technique.

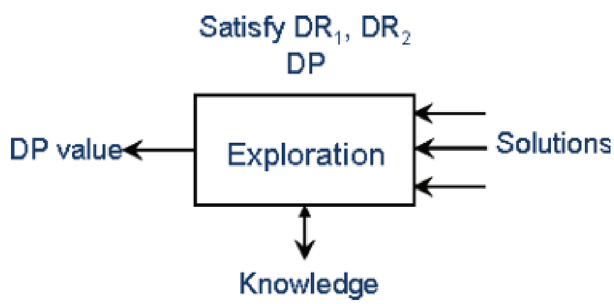

Fig. 3.: Bottom-up design exploration and evolution node

Moreover, unlike the top-down technique, the bottom-up strategy entails synthesis instead of decomposition. Comprehensive solutions are formed by combining detailed solutions, resulting in the composition of systems from individual partial solutions. The bottom-up design approach is typically characterized by a cyclical 'generate-and-evaluate' phase (9). A preliminary set of comprehensive solutions is developed and assessed to determine their suitability. Appropriate solutions are defined as solutions that satisfy the specified design requirements. New detailed solutions are developed to satisfy the design requirements based on their applicability. We learn about the acceptability of the solution and the relationships between the different sub-parameters as we develop and assess complete solutions. Future design challenges can be solved using the knowledge acquired. Information from past bottom-up initiatives may be used in the future to address design problems that were previously unsolvable using a top-down method. The following qualities dictate how the "bottom-up" design is developed:

(a) The design factors being taken into account;

(b) A range of potential solutions that may meet the design criteria;

(c) The available information or knowledge for evaluating the solutions;

(d) The information or knowledge generated through a bottom-up approach;

(e) The iterative process of generating solutions to determine the value of design parameters.

Deciding between top-down and bottom-up design

A simple picture shows how top-down and bottom-up design vary from one another. Examine the car's layout and design (10). The "top-down" method entails dissecting the car into its component subsystems after establishing the overall needs for the whole thing. Every subsystem has its requirements identified and broken down in a methodical manner. For example, a car's main need can be a certain level of acceleration. One way to analyze acceleration is as a separate engine power need. Then, each subsystem's unique needs are taken into account while designing the subsystems. In this instance, the engine will be specially made to have the necessary performance attributes. The first step in bottom-up development is to define the fundamental parameters that apply to the whole car. Bottom-up design attempts to meet each general need by assembling pieces and testing, as opposed to breaking a vehicle down into subsystems and specifying the criteria for each subsystem. For instance, to find the vehicle's acceleration, a motor may be fitted to the axle and wheels and measured. In this case, the vehicle's overall needs—like acceleration—are the determining factor rather than a particular subsystem's needs—like engine power. The components are changed and retested if the vehicle's acceleration isn't up to standard (11). Under a bottom-up method, the system is progressively built and early testing is conducted. Determining the best way for creating the design node is one of the design steps in the design process. Is it better to establish a design node using a bottom-up approach or a top-down approach for design breakdown and development? When choosing how to instantiate a design node, there are a number of factors to take into account. Is there sufficient data or expertise to identify the issue and move it up the hierarchy? A project parameter may be subdivided into many project parameters at higher levels of the hierarchy, each of which is regarded as a distinct issue. Nonetheless, comprehension of the connections between the many subproblems is required in order to deconstruct the issue and ascertain the prerequisites for the smaller problem. When designers use a bottom-up approach, they often lack connection understanding, which leads to the creation of relationship-related data. When tackling complicated design challenges with a large number of interconnected design jobs, there may be further justification for using a bottom-up paradigm. It might be challenging to oversee a big number of connected design components. Numerous scholars have examined the problem of large-scale designs' incapacity to forecast the effects of alterations when faced with a high number of interconnected design parts (12). Bar-Yam (11) proposed that under such conditions, a bottom-up evolutionary approach could be more suitable. It's critical to provide guidelines that assist design teams in selecting between top-down and bottom-up techniques while developing a computational design environment for the design process. Currently, the authors are developing quantitative methods to enhance decision-making on design progress.

As seen and discussed, choosing between the bottom-up or top-down approach might be tricky and time-consuming which is unsatisfying for business leaders and investors and at the same time stressful for engineers who are working to design a durable, reliable, manufacturable, safe, easy to maintain, environmental and cost-friendly product all at once so what could tidy up all this process?

Artificial Intelligence (AI)

There is significant interest in the ability of artificial intelligence (AI) to efficiently evaluate and react to the vast quantity of data that has been gathered (Figure 1).Studies benn undergoing since the 1950s. The main factors driving interest in artificial intelligence (AI) are advancements in the machine learning (ML) area and related fields like computer power and data storage. Numerous subjects have statistics demonstrating the potential of AI. Technology systems develop into useful instruments that may be used to boost productivity and make choices more quickly and logically (13). Therefore, it is anticipated that increased business and social use of AI and ML would have a positive impact.

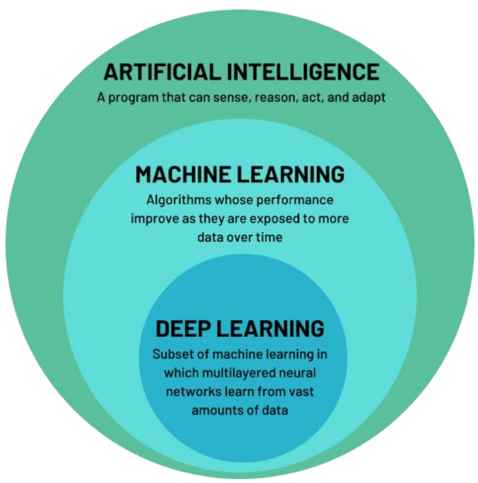

Fig. 4.: Artificial intelligence, machine learning, and deep learning.

Artificial intelligence is everywhere. It includes a wide range of theoretical and practical subfields, including self-driving vehicles, production, drawing, coaching, and the proving of theorems. Artificial intelligence (AI), which aims to replicate human behavior in machines, is one of the most fascinating and varied fields of computer science with a promising future. (14).

So, we can define AI as:

"It is a branch of computer science by which we can create intelligent machines which can behave like a human, think like humans, and able to make decisions." (14)

Artificial intelligence is the ability of a machine to perform human-based tasks such as learning, reasoning, and problem-solving. What's amazing about artificial intelligence is that, in contrast to preprogrammed machines, it is possible to create an autonomous machine using preprogrammed algorithms (15). AI is thought to be an old technology; in fact, some claim that, according to Greek mythology, there were mechanical men in antiquity who could work and act like humans (16).

Artificial Intelligence Objectives:

- Completing knowledge-based activities;
- Establishing the link between thoughts and deeds;
- Creating machines capable of carrying out activities requiring human intelligence;
- Developing intelligent systems that can learn new things on their own, behave intelligently, and show, explain, and counsel their users (14)

Artificial Intelligence's advantages:

There are many advantages to AI, but these are the principal ones:

Cutting down on human error: decisions made by artificial intelligence are based on data that has already been gathered and is processed through a series of algorithms. Errors are thus minimized, and the likelihood of attaining accuracy with a greater degree of accuracy rises quickly.ne of the biggest benefits of artificial intelligence is the transfer of risk from humans to the system. The advancement of AI can overcome many high-risk vocations, reducing the possibility of human harm or death. For instance, an AI-powered robot can mine coal and oil, travel to Mars, disarm bombs, explore the deepest regions of the ocean, and be a useful tool in any natural disaster.

Constant work: the typical individual puts in 4–6 hours a day without taking a break.

Nevertheless, smart machine can work all day every day without fatigueness or boredom as well as operating repetitive work infinitely.

Utilization of digital technology: every company and website have a customer support section where users can rely on for their queries, nowadays AI covers this role and its nearly impossible to identify that it’s not an actual human.

Faster decision-making: humans get carried emotionally in some decision-making moments and here’s where AI stand up where it plans and executes according to its code. (17)

Artificial intelligence's disadvantages:

There are major downsides to artificial intelligence as well, since every good thing has an equal and opposite. Here are a few instances:

Costly building expenses: Since artificial intelligence is always changing, hardware and software must be upgraded to match the most recent specifications. Machines and systems need costly upkeep and repairs. Furthermore, this technology is often unavailable for application because of the intricacy of the components and procedures.

Human laziness. AI enhances human laziness by automating much of the work, which in turn enhances laziness. People tend to depend on these developments, which may cause problems for later generations.

Growing joblessness: several companies already laid off many of its employees because of the capability of AI in replacing their low skilled jobs and we’re just getting started.

Absence of emotions: teamwork and human interaction is a very important aspect for the rise of companies and this is not the case while using AI.

Lack of thinking: Robots acts responding to their code and have no ability of “thinking outside the box”.

Machine Learning

In artificial intelligence, machine learning (ML) is the study and creation of statistical algorithms that can learn from data, generalize to new data, and carry out tasks without explicit instructions. Generative artificial neural networks have recently shown performance gains that exceed many earlier methods. As ML evolves the ask for data analysts is rising too in an interest of companies and businesses to sort out customers data and get insights. (18)

How Machine Learning Operates

Three components make up the machine learning algorithm-training system:

Process of making decisions: Classification and prediction problems are common applications of machine learning techniques. The method uses certain input data, which may or may not be labeled, to estimate the data pattern.

Error function: The error function is used to assess the model's prediction. If examples are provided, the error function may do a comparison to evaluate the model's correctness.

Procedure for optimizing a model: If the model is able to better match the data points in the training set, the weights are changed to reduce the difference between the model prediction and the known example. Until the algorithm achieves the required level of accuracy, it will continue to go through this assessment and optimization process while adjusting the weights.. (17)

Machine Learning Types

Machine learning can be classified as below in dependance of the work it is assigned:

Supervised learning is the process of training algorithms for accurate data categorization or result prediction using labeled datasets (see Figure 4). When more input data are introduced to the model, the weights are adjusted until the model fits the data appropriately. This is done as part of the cross-validation process to ensure that the model doesn't over- or under-adapt. Spam sorting into distinct inboxes is only one of the many real-world issues that businesses can solve using supervised learning.. Neural networks, naive Bayes, linear regression, logistic regression, decision trees, and other techniques are employed in this kind of learning (19).

Unsupervised learning uses machine learning techniques to examine and combine untagged samples (refer to Figure 5). Using techniques like PCA and SDV for dimensionality reduction and feature extraction, unsupervised learning algorithms find hidden patterns in data that are appropriate for customer segmentation, exploratory analysis, cross-selling tactics, and pattern recognition.

Learning that is semi-supervised is a compromise between learning with and without an instructor. In order to facilitate the classification and extraction of symptoms from a larger, unmarked dataset, it employs a smaller collection of labeled data during training. The issue of not having enough tagged data or not being able to afford to tag enough data to train a supervised learning algorithm can be resolved by partially supervised learning (see Figure 5) (20).

The goal of reinforcement learning is to behave in a way that maximizes compensation under certain conditions. It is used by robotics and software to determine the optimal behavior or course of action in a given circumstance. In rewarded learning (see Figure 6), the task's completion is decided by the system without any input from the user and without any learning. In contrast, the solution key is included in the training data for supervised learning, meaning that the model is trained using only the right response. If there is no training set available, the system is compelled to learn by experience. (18)

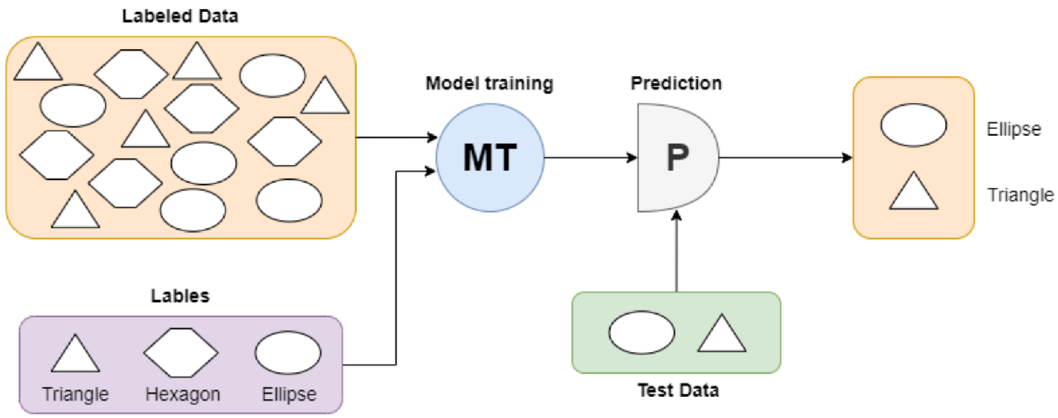

Fig. 5.: Supervised machine learning (18).

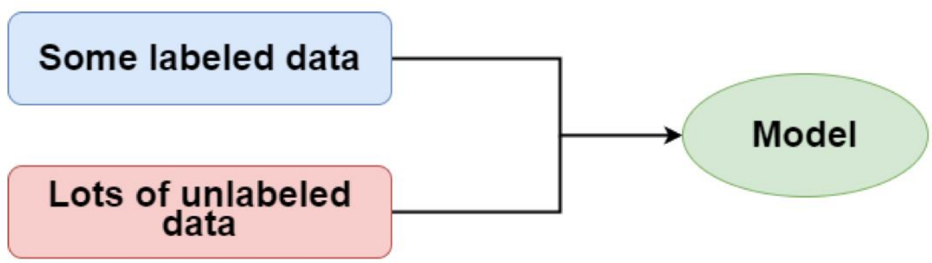

Fig. 6.: Unsupervised machine learning (18).

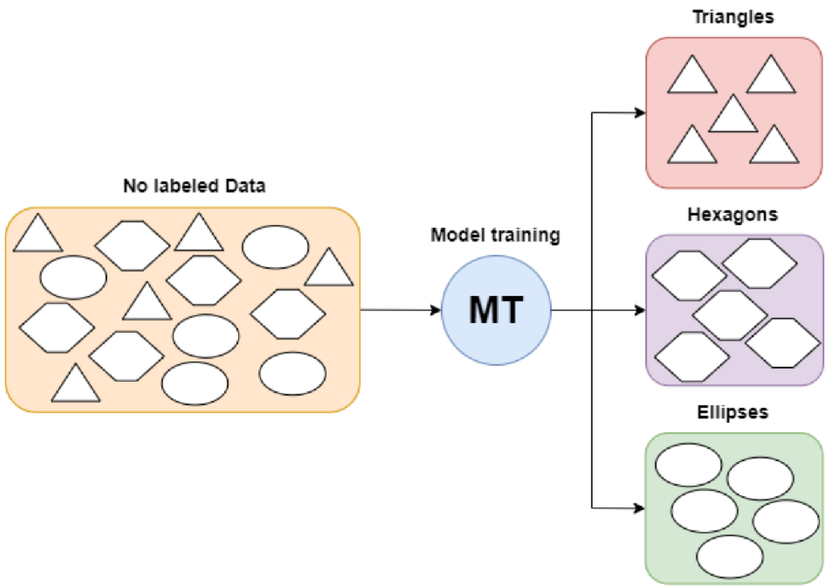

Fig. 7.: Semi-supervised machine learning (18).

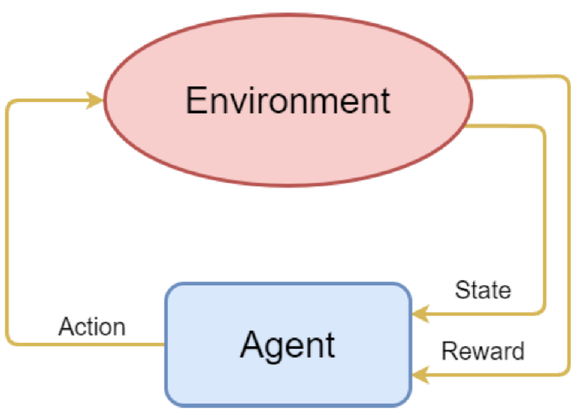

Fig. 8.: Reinforcement learning (18).

Deep Learning

Deep learning (DL) is a subset of machine learning (see Fig. 3), which is a subset of artificial intelligence. Using humans' logic ways of thinking inspired by the neural structure of the brain and processing data, deep learning has the ability to surf its algorithms and output human like behavior (21). Deep learning algorithms use a pre-established logical framework to attempt to get comparable results as continuous data analysis. Neural networks are multi-layered mathematical structures that are used in deep learning.

Machine Learning and Deep Learning

Deep learning (DL) and machine learning (ML) are not alike neither by the way they're developed or by the outcomes it can give, and while this technology is taking over the world many mistaken one for the other where deep learning is a subset of machine learning (Fig. 1)

For good performance, DL (Deep Learning) necessitates a substantial quantity of labeled samples for data consumption. However, the quantity of data alone is insufficient; it must also possess the appropriate quality, meaning it must be accurately classified. Not all collected data is appropriately marked, categorized, or formatted for deep learning (22). Public access to such data is not always guaranteed. Data labeling in this scenario necessitates meticulous and costly efforts, frequently entailing a well-defined and strict set of protocols, quality control measures, and specialized skills. Regrettably, the significance of this truth and its influence on the practicality of DL for real-world issues is sometimes underestimated in DL conversations.

The training phase of deep learning systems typically necessitates the use of specialized hardware, such as graphics processing units (GPUs), to significantly decrease the execution time to a feasible duration, typically ranging from hours to weeks, as opposed to years (23). Despite the decreasing cost, these systems remain very expensive when compared to the requirements of more basic machine learning kits.

Specification extraction involves integrating domain expertise into the development of extractors for specific specifications. This is done to simplify data complexity and reveal patterns that can be used by learning algorithms. This method is both laborious and costly.

Figure 9 illustrates a discrepancy in specification extraction between DL (Deep Learning) and ML (Machine Learning).

Deep learning is more expensive in terms of time, hardware, and data compared to other applications. To summarize, those 2 revolutionary technologies are best represented and used in accordance with the criteria outlined in Table 1 (24).

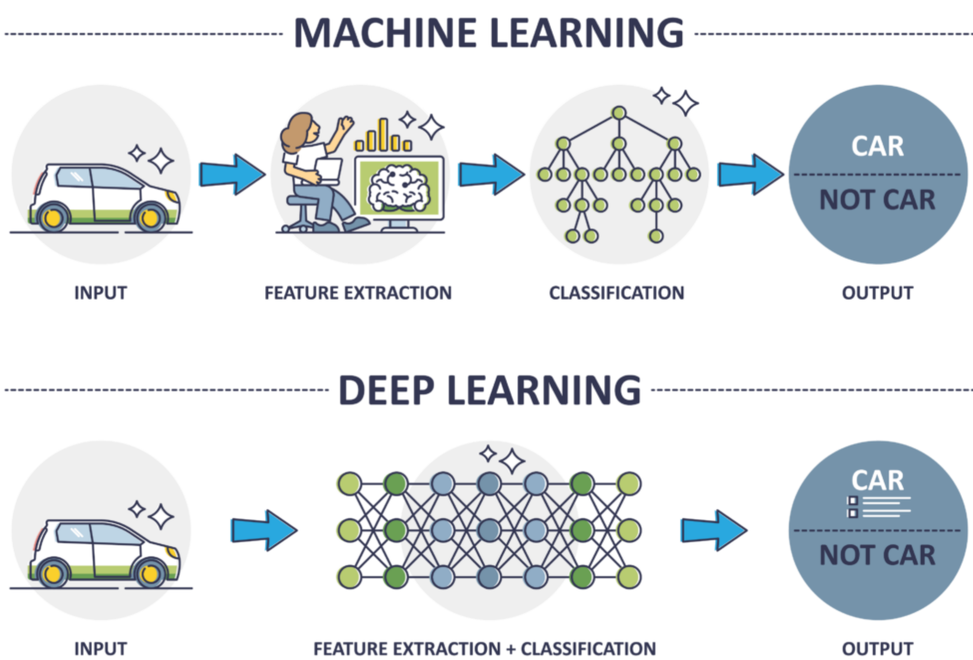

Fig. 9.: DL and ML operations process (25).

Criterion	**Machine Learning**	**Deep Learning**
Data volume	Fewer data	Large amounts of data
Computational costs	Shorter time and cheaper hardware.	Longer time and more expensive hardware.
Adaptability	In order to build models that achieve superior performance, it is necessary to employ methodologies that are tailored to the specific domain and application, as well as using specialist engineering techniques. Consequently, the resulting models exhibit reduced adaptability, even within similar domains.	It is easier to adapt to different areas and applications.
Engineering tools	Because there aren't enough experts in the subject, complex specialized engineering is frequently needed, which takes time and money.	It has the potential to reduce or eliminate the need for a comprehensive specification, thereby reducing the time and costs involved with this phase. Nevertheless, deep learning techniques may result in higher expenses related to hardware and time.
Interpretability	Thanks to expert engineering and a streamlined design, systems are frequently straightforward to understand. Understanding the process and rationale behind the ML algorithm's decision is more straightforward. This is essential for updating and fixing a system that produces erroneous results in unexpected circumstances.	More difficult to interpret. It is commonly considered a "black box" system, in which researchers strive to elucidate the mechanisms and rationale behind the production of specific outcomes. However, significant progress is still being done in this area, revealing the inner workings of a complex system, which may eventually diminish this distinction.

Table. 1.: Applications of ML and DL (26)

Datasets

Datasets are essential elements in machine learning, serving as the primary source of raw data that machine learning algorithms utilize to identify patterns and generate predictions. A dataset is a group of data points that possess shared features, and machine learning algorithms utilize these datasets to acquire patterns and generate predictions. Datasets can exhibit diverse formats and serve a multitude of purposes. Certain datasets are derived from sensors or other data acquisition equipment, but others may be obtained via scraping websites or aggregating from other sources (27). The caliber of the dataset a machine learning algorithm uses for training has a significant impact on the algorithm's performance. Similar to cooking, the quality of the predictions (recipe) increases with the quality of the materials (data). The same way that employing subpar ingredients might result in a bad dinner, the algorithm will find it difficult to produce accurate predictions if the data is inadequate or irrelevant. (28). The dataset must exhibit representativeness with regards to the topic at hand and possess sufficient magnitude to furnish the algorithm with ample data for learning purposes. Furthermore, dataset diversification and preciseness are a crucial aspect for its algorithm to process circumstances and guaranteeing the algorithm's ability to extrapolate to novel circumstances. Ultimately, it is crucial to thoroughly assess the efficacy of a machine learning algorithm when employing the selected dataset. The procedure comprises separating the training and testing sets from the dataset. The algorithm is then trained on the training set, and its performance is evaluated on the testing set. The selection of evaluation metrics will vary depending on the particular situation at hand, while often employed metrics encompass accuracy, precision, recall, and F1 score (19).

Images and video datasets

Machine learning models are trained on collections of visual data called image and video datasets. Both the size and organization of these datasets might vary. They are used in many different tasks, including as facial recognition, object identification, motion tracking, and emotion detection.

ImageNet (29) is a highly renowned dataset for videos and photos, comprising millions of images that are categorized into over 20,000 different classes. ImageNet has been utilized for training several deep learning models, such as convolutional neural networks (CNNs), specifically designed for tasks involving image identification.

Additional well-known datasets for videos and photos include COCO (Common Objects in Context) (30), which comprises images annotated with object categories and segmentation masks, and Open photos, which encompasses millions of images with annotations for object recognition and segmentation. Furthermore, there exists plenty of specialized datasets tailored for certain uses, in addition to the aforementioned general-purpose datasets (31). As an illustration, the Labeled Faces in the Wild (LFW) dataset comprises facial photos that have been extensively employed in facial recognition studies, whereas the Kinetics dataset is a vast collection of videos specifically created for action recognition purposes.

CAD and CAD-Based Datasets

Datasets utilized in computer-aided design software, such as CAD models, CAD files, and other design-related information, are referred to as computer-aided design-based datasets. These datasets may be used for many different things, such as building 3D models, developing goods, and working in the engineering and architectural sectors.

CAD files are available in several forms, including AutoCAD, SolidWorks, and CATIA, and can be utilized to generate models for diverse applications. For example, computer-aided design (CAD) data can be utilized to generate digital prototypes, conduct virtual testing, and do simulations. CAD-based datasets are highly advantageous for machine learning applications, including generative design, shape optimization, and design automation.

Notable CAD-based datasets

Fusion 360 Gallery Dataset (32): The Fusion 360 Gallery Dataset comprises comprehensive 2D and 3D geometric data obtained from parametric CAD models. The reconstruction dataset offers a number of building process data for a number of simple designs made using 'draw and extrude' methods. The segmentation dataset classifies 3D models, including those in formats like B-Rep, mesh, and point clouds, according to the CAD modeling process they go through.

ModelNet (33): The database has more than 127,000 3D computer-aided design (CAD) models belonging to 662 different object categories. These models have been consistently aligned and normalized to fit into a unit sphere. The dataset is divided into two sets: a training set and a testing set. The models are labeled with class labels to facilitate supervised learning.

ABC (34): This dataset consists of a large collection of CAD models specifically designed for the purpose of geometric deep learning. With almost a million precise geometric models, this dataset is utilized for geometric deep learning. Dependable ground truth data, such as patch breakdown, well-defined annotations of distinct features, and computed differential characteristics, are included with every model.

3D ContentCentral (35): 3D ContentCentral is a portal that offers complimentary 3D CAD models of industrial components, including gears, bearings, and motors. The platform provides a wide range of models available for download in various formats, including SolidWorks, AutoCAD, and Inventor.

McMaster-Carr (36): McMaster-Carr is a platform that offers complimentary 3D CAD models of mechanical components, including bearings, screws, and gears. The portal offers an extensive array of models available for download in multiple formats, such as SolidWorks, AutoCAD, and Inventor.

TraceParts (37): TraceParts is a platform that offers complimentary 3D CAD models of industrial components, including pumps, motors, and valves. The portal offers an extensive assortment of models that can be downloaded in multiple formats, such as SolidWorks, AutoCAD, and CATIA.

Machine Learning in Mechanical Design and Optimization

Machine learning is the process by which computers learn by analyzing data. This method has a great deal of applications in mechanical engineering. Expert machine builders have amassed a vast amount of knowledge through case studies and improved procedures. By using their technical expertise to familiar components that have already been investigated, or by drawing on their experience to pick up new skills and adjust to new obstacles, they can tackle new challenges in two ways. Beginners in this field gain knowledge and improve their effectiveness through this approach. In the realm of engineering education, a substantial part of learning happens while working. The amount of compensation depends on one's ability to collect and interpret data (38).

Product design

Machine learning has the potential to enhance the design of machines and equipment through the integration of several parallel studies, such as physics, solid mechanics, fluid mechanics, and others. Neural networks can be employed to train a computer to accurately differentiate between distinct components, assemblies, and tools. This acquired knowledge can then be utilized in the future for creating a diverse array of components and for efficient data entry in the mass production of different goods. The subsequent subchapters present comprehensive research endeavors conducted worldwide that focus on the integration of artificial intelligence and machine learning in the field of mechanical building and design (39).

3D Generative-Adversarial Modeling for Machine Learning of Object Shapes

This paper proposes a new framework called the 3D generative inverse network (3D-GAN) that utilizes current advancements in volume convolutional networks and generative reverse networks to construct 3D objects from probability space. Please refer to Figure 11 for visual representation. The proposed model offers three distinct advantages. Firstly, it employs an inverse criterion instead of traditional heuristic criteria, allowing the generator to implicitly grasp the object's structure and produce high-quality 3D objects. Secondly, the generator establishes mappings from a low-dimensional probability space to 3D object space, enabling the generation of objects without the need for a reference image or CAD model, and facilitating the exploration of the diversity of 3D objects. Lastly, the proposed model is versatile and can be applied to a wide array of applications. The experiments confirm that the proposed strategy produces 3D models of superior quality. Additionally, the acquired attributes using unsupervised machine learning exhibit outstanding performance in accurately identifying 3D objects, comparable to the performance of supervised learning methods (40).

Fig. 10.: The 3D reconstruction of images on a dataset from IKEA (40)

Generative Design and Verification of 3D Conceptual Wheel Models

This study aims on an engineering design that integrates artificial intelligence (AI) with computer-aided design (CAD) and computer-aided engineering (CAE). This study presents the development of a CAD/CAE framework utilizing deep learning techniques for the initial design stage. The framework is capable of generating 3D CAD drawings and doing technical performance analysis automatically. The suggested framework involves multiple stages, including investigating two-dimensional generative design, decreasing dimensionality, running experiments in latent space, automating the generation of three-dimensional CAD models, modeling the results of CAE automatically, utilizing transfer learning, and carrying out visualization and analysis. An example of this is provided by a case study that centers on road wheel design (Fig. 13), the framework shows that AI can be feasibly incorporated into a project for designing a final product (41). With this framework, engineers and industrial designers can collectively evaluate a vast array of 3D CAD models alongside the AI-predicted technical performance analysis (CAE analysis). This enables them to identify the most optimal conceptual design variations for the subsequent phase of detailed designs (41).

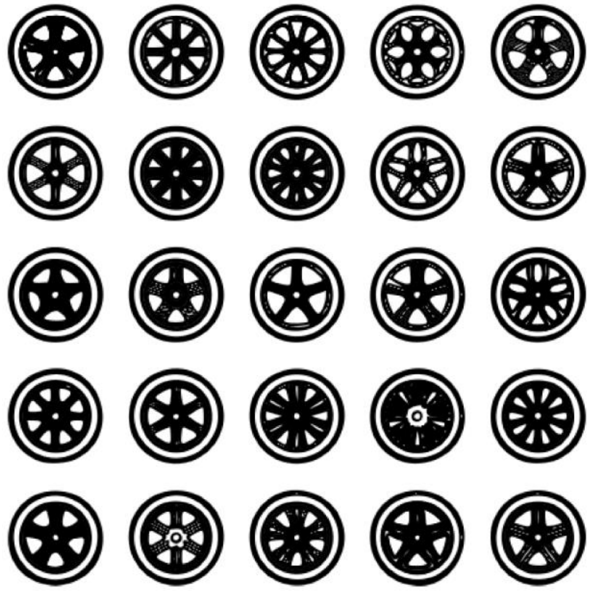

Fig. 11.: Automatic generation of 2D wheel disk images (41)

Visual Search Application for Machine Components

This study aimed to produce a comprehensive, labeled set of mechanical parts in order to facilitate their identification and classification. It displays an extensive set of three-dimensional objects that depict mechanical parts (see Figure 16). For doing real-world research on the features and behaviors of mechanical components, this dataset is very helpful. Applications in computer vision and industry require an analysis of these components' form descriptors. Nevertheless, there appears to be a deficiency in the creation of these mechanical component-specific annotated datasets.

Since accurate mechanical component annotation necessitates specialized knowledge, collecting 3D models has proven to be a barrier in the creation of this collection. Three things constitute this study's main contributions: It starts by gathering a large collection of mechanical components with annotations. Secondly, it creates a tiered structure for grouping these elements. Finally, it assesses how well deep learning classifiers can analyze these mechanical components' forms (42).

In addition, seven sophisticated deep learning classification techniques are analyzed and classified into three categories in the study: point clouds, volumetric representations in voxel grids, and representation-based techniques. Autodesk, a company well-known for its Design Graph software, is carrying out related studies in this field. This suggests that the discipline of mechanical component analysis and classification is seeing an increase in interest in and demand for these kinds of investigations. (43).

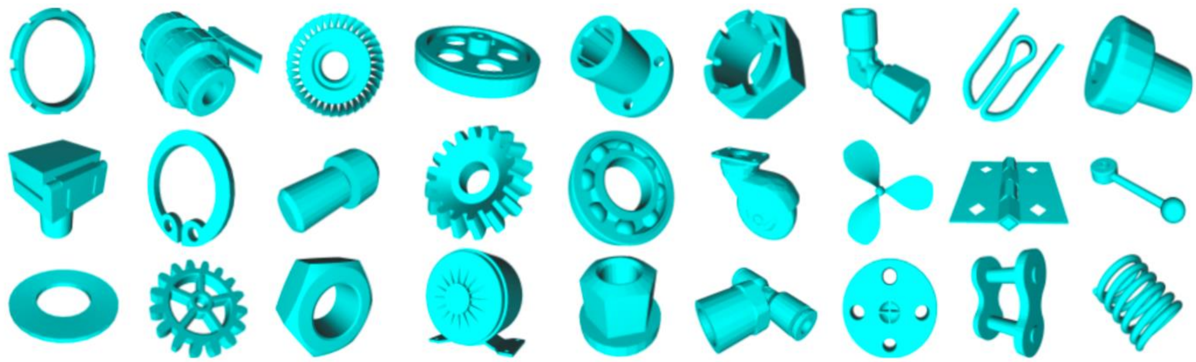

Fig. 12.: Machine parts database (44).

Handlebar neck in bike parts

The handlebar neck, is an integral component of the bicycle that experiences frequent usage. It is designed with the support of artificial intelligence. This research looks at a part that serves as a link between things and helps steer and control bicycles. Its purpose is to transfer the rider's control over movement from the handlebars to the shaft that connects to the front wheel. Artificial intelligence (AI) is used in the component design process to make sure, within material limits, that the component has the necessary mechanical strength and is appropriate for the planned manufacturing process.

Using Autodesk's Fusion 360, a CAD program with AI capabilities included, the design was produced. This software uses AI to support the design process and accepts basic CAD data input. By incorporating AI to improve the design for both functionality and manufacturability, it aids in the crafting of the component by accounting for the relevant parameters and restrictions. This method demonstrates how artificial intelligence (AI) can be used to improve and streamline the design of intricate mechanical components.

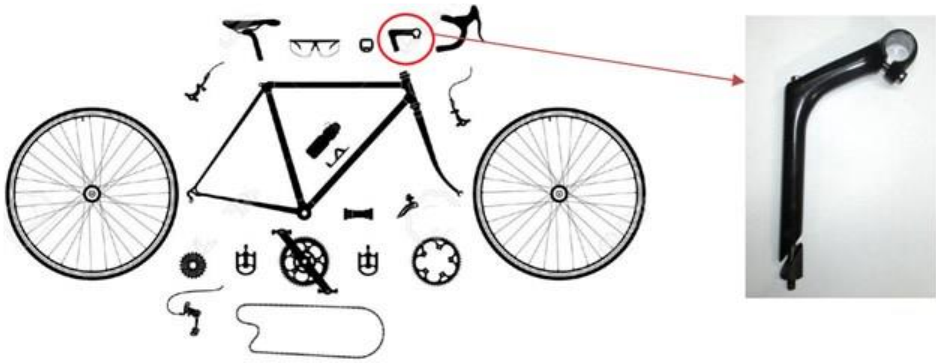

Fig. 13.: Handlebar neck in the parts of the bike (45)

In this project, a visual model of a key bicycle component - the main shaft that connects the steering and front wheel, and to which the handlebar neck attaches - was developed using Fusion 360 software, as illustrated in Figure 14(a). During the initial phase, there was a discussion about which areas of the component are essential and which are not critical for the new design. This step was important to identify the parts of the component that are necessary for its function and structural integrity, and those that could be modified or removed without affecting performance, leading to an efficient and effective design process. Therefore, as depicted in Figure 14(b), the areas that were intended to be part of the design were represented in green, while the areas that were not intended to be part of the design were represented in red. Therefore, when constructing the program model, its boundaries are established.

Fig. 14.: Modeling the design criteria of the bicycle part: a) region where the model will be created, b) desired and unwanted parts in the design (45)

Ensuring the durability of the model was a primary concern during the design phase. The mechanical limits and applied forces were precisely determined as part of the design parameters. The goal of this careful planning was to ensure that the model could withstand these preset limitations. The static portions of the model and the force application locations are indicated in the visual depiction presented in Figure 15, together with their corresponding magnitudes. The main goal of this design strategy was to create a model that would be able to endure expected stresses and still be functional and structurally sound in real-world situations.

In formulating the model under specific load and boundary conditions, multiple criteria can be proposed. The first criterion involves a comparison of the intended model with the chosen materials, focusing either on minimizing the weight or on optimizing for maximum strength. The second criterion relates to the chosen manufacturing method. For this project, the model needed to meet two key requirements: it should have a minimal weight while maintaining a safety factor of at least 2 in terms of strength. Additionally, the design of the proposed model must align with the guidelines detailed in Figure 16, with the production process utilizing a 3D printer. This approach ensures a balance between lightweight design and structural integrity, adhering to specific manufacturing capabilities.

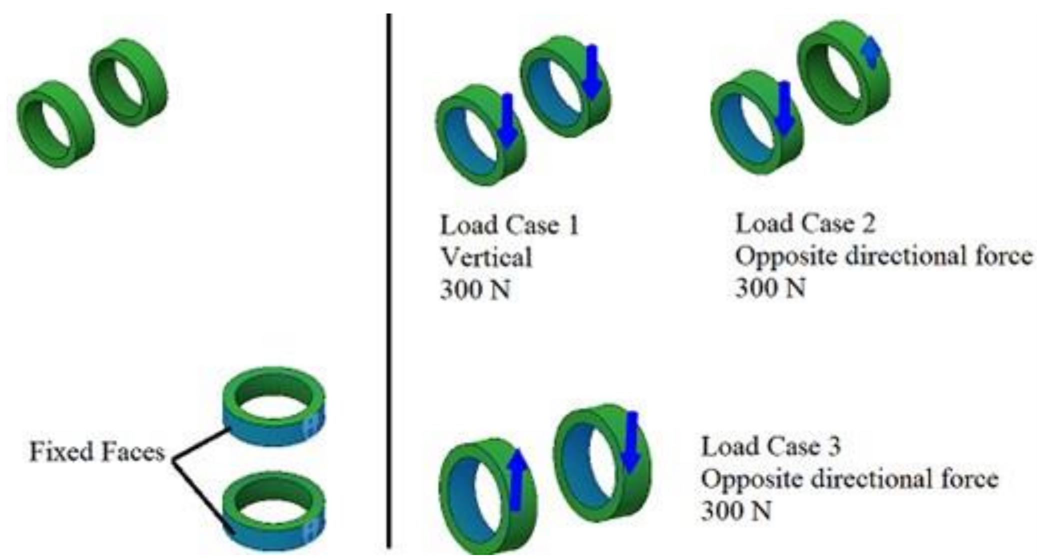

Fig. 15.: Defining the boundary conditions and loads in the design of the bicycle part (45)

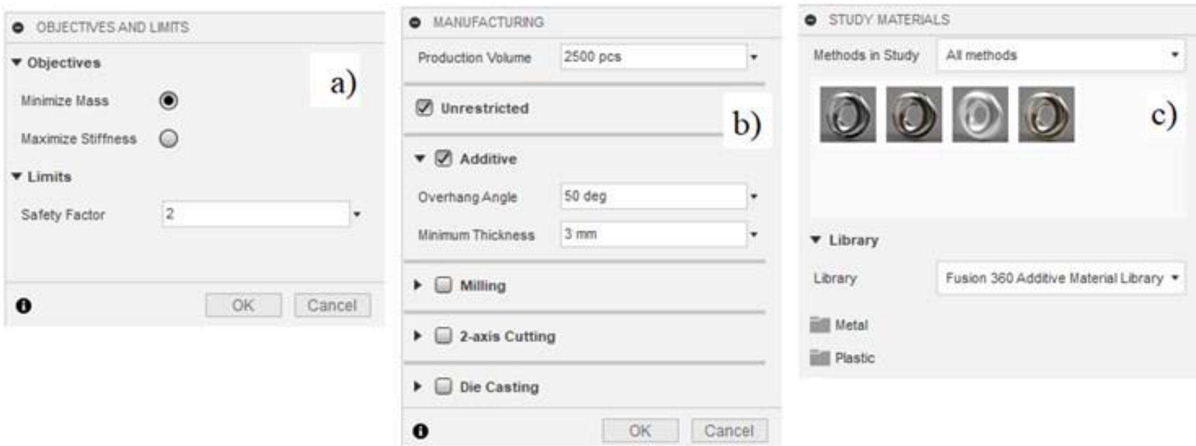

Fig. 16.: Determining the design criteria of the model (45)

Generative design, an AI-supported design approach, yielded 16 distinct outcomes, in contrast to conventional design methods. The algorithm generated these results solely based on the provided information, including the geometry description, loading and boundary conditions, various material kinds, and manufacturing variations. These findings replicate natural phenomena in the modeling of the traditional designer. These findings offer the designer other models that can be examined.

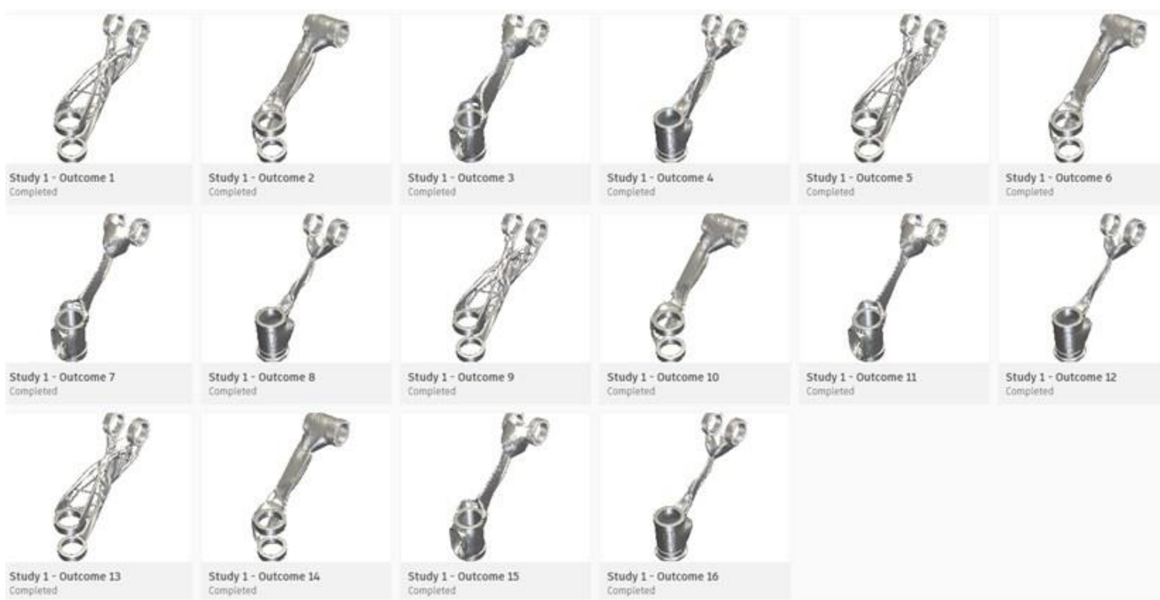

Figure 17: Artificial Intelligence supported design models (45)

Revolutionary application of AI in mechanical engineering

AI in manufacturing

By facilitating automation, enhancing quality assurance, and streamlining production procedures, artificial intelligence is revolutionizing the manufacturing sector. Mechanical engineers can increase productivity and efficiency in production by using AI technologies to streamline processes.

Automated quality control:

Automation of manufacturing quality control procedures is possible with AI-powered solutions. Real-time defect and anomaly detection is possible using AI algorithms through the analysis of data from cameras and sensors. This technology can spot problems that human operators might find challenging, which improves product quality and lowers waste. Automated quality control systems can also offer insightful information for process optimization, assisting producers in pinpointing areas for enhancement and boosting productivity (46).

Predictive maintenance:

In the manufacturing sector, predictive maintenance is revolutionizing the practice. Mechanical engineers can schedule preventive maintenance and anticipate when equipment will break by utilizing AI algorithms to examine sensor data. This strategy lowers maintenance costs and minimizes unscheduled downtime. Manufacturers can increase overall operating efficiency, prolong equipment longevity, and optimize maintenance schedules by utilizing AI (46).

Optimized production planning:

AI can analyze demand projections, historical data, and other pertinent variables to optimize production scheduling. AI algorithms are able to create production plans that optimize productivity and reduce expenses by taking into account a variety of restrictions, including personnel availability, machine capacity, and material availability. Thanks to this technology, producers can react swiftly to shifting market conditions and allocate resources optimally, which boosts output and increases customer satisfaction (46).

AI in robotics

AI is transforming robotics by giving machines the ability to see, understand, and decide for themselves. AI-powered robots in mechanical engineering can carry out difficult jobs with accuracy and efficiency, boosting output and enhancing safety.

Collaborative robots:

Cobots, or collaborative robots, are made to operate side by side with people in a shared office. These robots can recognize and react to human motions and commands because they are outfitted with artificial intelligence (AI) systems. Cobots can help human operators in mechanical engineering with activities including material handling, assembly, and inspection. Cobots can collaborate with humans and adjust to changing situations by utilizing AI, which increases safety and productivity in production settings (47).

Autonomous robots:

Robots that are autonomous are able to complete tasks without assistance from humans. Autonomous robots in mechanical engineering can perform activities including welding, material handling, and inspection. These robots have AI algorithms installed in them, which allow them to see their surroundings, decide what to do, and move through challenging areas. Autonomous robots can function more precisely and efficiently by utilizing AI, which lowers the need for human intervention and boosts total output (47).

Robotics process automation:

Robotic process automation (RPA) is a technology that automates repetitive and rule-based operations using artificial intelligence (AI) algorithms. RPA can be used in mechanical engineering to automate processes including report preparation, documentation, and data entry. RPA systems can evaluate data, make decisions, and complete jobs quickly and accurately by utilizing AI. Thanks to it, human engineers are able to concentrate on more intricate and imaginative projects, which boosts output and increases job satisfaction (48).

AI in energy efficiency

AI is a key component in mechanical engineering's efforts to increase energy efficiency. Engineers can optimize energy use, minimize waste, and create sustainable solutions by utilizing AI technologies.

Energy management systems:

Energy management systems with AI capabilities can optimize energy use in commercial and residential buildings by analyzing data from sensors and meters. These systems can modify energy usage in real-time to decrease waste and lower expenses by taking into account variables like occupancy patterns, weather, and equipment efficiency. AI systems are also capable of spotting chances for energy savings and making suggestions for enhancements. Engineers may achieve huge energy savings and contribute to a more sustainable future with the help of AI-powered energy management systems (49).

Smart grid optimization:

By evaluating data from several sources, including power plants, renewable energy sources, and customer demand, artificial intelligence (AI) can maximize the performance of smart grids. AI algorithms can optimize electricity distribution and balance supply and demand by taking into account variables like electricity costs, weather, and grid reliability. With the use of this technology, engineers may successfully integrate renewable energy sources, lower energy losses, and increase grid efficiency (49).

Energy efficient HVAC systems:

AI can enhance energy efficiency by optimizing the functioning of HVAC (heating, ventilation, and air conditioning) systems. Artificial intelligence (AI) algorithms can modify HVAC settings in real-time to ensure maximum comfort while consuming the least amount of energy by evaluating data from sensors and weather forecasts. Additionally, this technology can suggest energy-saving actions and spot chances for equipment improvement. Engineers may create and manage HVAC systems that cut down on energy waste and support sustainable building practices by utilizing AI (49).

AI in product lifecycle management

Product lifecycle management (PLM) is being revolutionized by AI, which gives engineers the ability to increase decision-making, collaborate better, and streamline procedures all the way through the lifecycle of a product.

Automated documentation:

Technical documentation can be generated automatically by AI-powered systems, saving time and effort compared to manual documentation activities. AI systems are capable of producing precise and standardized documentation, including assembly instructions and user manuals, by evaluating product data and standards. This technique raises the standard of mechanical engineering documentation overall, decreases errors, and increases efficiency (50).

Collaborative design:

Engineers can collaborate easily, no matter where they are physically located, thanks to AI-powered technologies. These tools enable effective collaboration throughout the design process by facilitating version control, document sharing, and real-time communication. Engineers may work together more productively, share information, and make wise judgments by utilizing AI, which will enhance product quality and accelerate time to market (50).

Decision support system:

By analyzing data from several sources and offering insights and recommendations, artificial intelligence (AI) can improve decision-making in product creation. AI algorithms can help engineers make well-informed decisions by taking into account elements like cost analysis, customer input, and market trends. Engineers may now analyze risks, compare design options, and improve product development tactics thanks to this technology. Engineers may improve decision-making, shorten time to market, and enhance overall product performance by utilizing AI (50).

AI in safety and risk assessment

AI is enabling engineers to discover possible hazards, evaluate risks, and create efficient mitigation solutions, which is a critical function it plays in safety and risk assessment in mechanical engineering.

Hazard identification:

Artificial Intelligence algorithms have the capability to examine data from multiple sources, including sensor data and past incident logs, in order to detect possible risks in mechanical systems. Engineers can identify trends and abnormalities that could point to possible safety concerns by utilizing AI. With the use of this technology, mechanical engineers can now more effectively detect potential risks, put preventative measures in place, and increase overall safety (51).

Risk assessment

By evaluating data from several sources and offering insights on potential hazards and their effects, artificial intelligence (AI) can improve risk assessment. Artificial intelligence algorithms are capable of evaluating risks and prioritizing mitigation activities based on variables including probability, severity, and exposure. With the use of this technology, engineers can plan ahead, deploy resources efficiently, and lessen the chance and consequences of mistakes or malfunctions (51).

Optimizing safety

AI systems that analyze data and spot areas for improvement can maximize safety precautions. Artificial intelligence (AI) algorithms can suggest safety improvements that reduce risks and enhance overall safety performance by taking into account variables including incident reports, near-miss data, and safety laws. With the use of this technology, engineers can lower the number of accidents, enhance safety procedures, and make workplaces safer (51).

Challenges and Limitations

The Crucial Role of Data in Machine Learning

Machine learning models, which are sometimes compared to engines, run on data. The availability of sufficient and high-quality data is a prerequisite for the effectiveness of these models. Still, a number of important queries come up in this situation:

- Data Quantity and Quality: One of the main concerns is figuring out how adequate the data is. The performance of the model is heavily influenced by the quality of the input data. Inaccurate or untrustworthy results may result from inadequate or poor-quality data.
- Data Processing and Acquisition: Gathering data is a challenge for researchers. They have two options: they can use already-published works and databases, or they can use high-throughput simulations or experiments to produce their own data. Making sure the data covers a major amount of the design area presents a considerable problem in this case. Applying ML may be unfeasible or too burdensome in situations where data collecting is either too easy or too difficult.
- Preprocessing Requirements: Unprocessed data is frequently understandable to people but difficult for computers to analyze, particularly when it comes to text or image formats. Preprocessing data is therefore required in order to prepare it for machine learning models. It emphasizes how crucial it is to use mechanical engineering domain expertise to gather representative data and carry out appropriate preprocessing, which will improve the performance of ML models.

Integration Challenges with Mechanical Engineering Systems

- Complexity of Mechanical Processes: There are many complex processes that fall under the umbrella of mechanical engineering. These intricacies may be difficult for ML and AI algorithms to effectively model, which could result in inaccurate findings that are challenging to correct.
- System Integration and Manual Intervention: Systems in mechanical engineering

frequently call for a great deal of manual intervention. It is difficult to integrate AI and ML into these systems since it may interfere with established procedures and decrease productivity.

- Subject Expertise is Needed for Data Handling: In mechanical engineering, obtaining, preparing, and analyzing data for use in machine learning models necessitates in-depth subject knowledge. This knowledge is essential to ensuring that the models are trained successfully and that the data appropriately depicts the mechanical processes.
- Managing AI and Human Oversight: In mechanical engineering, the use of AI and ML must be tempered with human oversight. Even though many processes can be automated and optimized by these technologies, they cannot completely replace an experienced engineer's ability to recognize subtleties and make sound decisions (52).

Data is the gasoline that powers machine learning (ML) models, if they are the engines that can tackle different jobs. The models must have enough data in order to function, and the models must function well with high-quality data. However, a number of important and challenging concerns come up, such as: how much data is sufficient? How are those data obtained? How good is the input data quality? And how can it be made better? These are important concerns because the data connects the relevant mechanics problems to the applied ML models, which is essential for ML-based mechanical material design (53). Researchers have two options for gathering data: they can use pre-existing databases or the literature, or they can create their own databases by using high-throughput simulations or experiments (Fig. 16). The following dilemma typically arises when raw data is fed into an ML model: if the data is too easy or too hard to collect, applying ML-based approaches to solve the problem would be pointless or challenging. One common scenario is that the obtained datasets cover only a tiny percentage of the design space, in which case there is no need to utilize machine learning (ML). Another common scenario is that the existing approach can traverse the full design space at an acceptable cost. Another possibility is that the textual or image databases gathered are intelligible to humans but not to machines. In those situations, the raw data must typically be preprocessed before being fed into the machine learning model. This highlights the significance of utilizing the researchers' domain expertise to obtain representative data and properly conduct data preprocessing for improved ML model outcomes (54) (55). Additionally, there are many intricate processes involved in mechanical engineering, and machine learning and artificial intelligence algorithms might not be able to adequately represent these processes. This can produce unreliable findings and be challenging to debug, moreover, systems in mechanical engineering are frequently intricate and necessitate much manual labor. Because of this, it may be challenging to incorporate AI and machine learning into current systems without interfering with productivity (56).

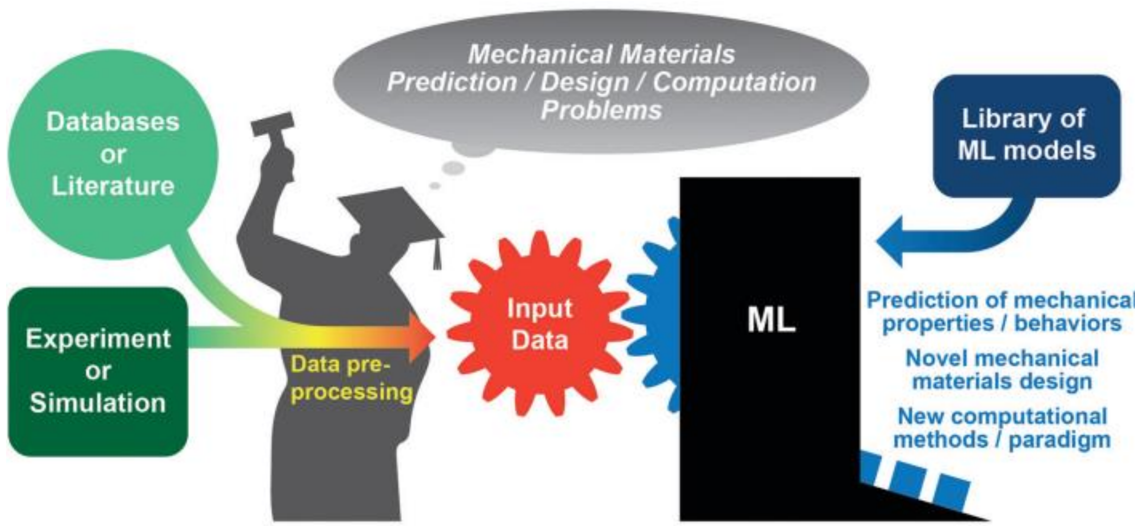

Figure 18: Schematic of a typical workflow for design of mechanical materials using ML (57)

Ethical considerations

The idea that philosophy has no place in engineering is a frequent one. But as sophisticated technologies like artificial intelligence proliferate, it's critical that engineers and philosophers carefully weigh the ethical ramifications. Automation presents serious ethical problems that should be carefully considered. As machines start to fill jobs that people have historically filled, a number of worries surface. These consist of how it will affect jobs, how decision-making procedures will change, and how it will affect society as a whole. The ability of artificial intelligence (AI) to do intricate jobs and arrive at seemingly simple conclusions requires a thorough assessment of the ethical considerations entwined with mechanical engineering technical breakthroughs. The confluence of technology and ethics highlights the necessity of approaching the creation and application of AI in engineering from a comprehensive perspective.

The moral landscape of automation

In the domain of mechanical engineering, artificial intelligence (AI) ethics refers to the moral precepts and rules that direct the creation, application, and use of AI in mechanical systems. This idea is essential to creating a positive interaction between ethical concerns and technological progress. It includes all of the moral difficulties and obligations that come with developing intelligent systems that communicate and work in tandem with human endeavors. AI ethics provides a framework for guidance in the field of mechanical engineering, helping engineers navigate the murky moral waters. It assists in achieving a balance between the advancement of technology and moral contemplation, guaranteeing that the development of technology is in line with moral principles and the welfare of society. The ethical implications of AI-driven mechanical engineering on jobs and human responsibilities are a crucial aspect to consider. As machines perform jobs that were previously performed by humans, worries regarding job displacement and the redefining of professional roles surface. Although the application of AI to mechanical processes has the potential to completely transform businesses, it also raises moral concerns about the effects of broad automation on society (58).

The consequences of Ethical Errors in AI-Powered Mechanical Engineering

There is a greater chance of unethical behavior in mechanical engineering as artificial intelligence advances. Not alone are ethical issues theoretical; they also serve as barriers against unanticipated outcomes and social unrest. There can be serious consequences in AI-driven mechanical engineering when ethics are not given enough thought. For example, trust in automated systems might be damaged by opaque decision-making procedures. In a similar vein, algorithms that are prejudiced may help injustices continue. In order to ensure responsible and equitable use of technology, these scenarios highlight how crucial it is to incorporate ethical issues into the development and application of AI in mechanical engineering.

Investigating these possible hazards is essential for preventative actions that protect against unexpected outcomes. To ensure that the advantages of AI in mechanical engineering are achieved without sacrificing society norms, it is necessary to take a proactive approach in recognizing, addressing, and repairing ethical flaws. In order to proceed with AI in engineering, one must have a thorough awareness of the ethical implications of automation. To appropriately navigate the changing landscape of AI-driven mechanical engineering, engineers and stakeholders need to understand this as much as this theoretical conversation (59).

Ethical challenges

The threat of bias in AI algorithms is one of the ethical issues that AI-driven mechanical engineering raises. Automated systems' underlying algorithms may unintentionally reinforce or even magnify social prejudices seen in training data. Biases can take many forms, including those based on socioeconomic status, gender, or race, which can undermine the justice and fairness of AI-driven mechanical procedures.

In order to reduce discrepancies, engineers need to be aware of the biases in training datasets and use strategies like data augmentation and algorithmic corrections. It is crucial to incorporate diversity and inclusion principles during the development phase to guarantee that the final product complies with moral guidelines and encourages equity among various user groups. Transparency and accountability become critical when automated systems assume decision-making responsibilities in mechanical engineering (60).

The black-box nature of sophisticated AI systems makes it difficult to comprehend how judgments are made, as noted by Gaber (61).

Lack of transparency in AI systems, particularly in mechanical engineering, can cause confidence to decline and make it difficult to find and fix biases or mistakes in these systems. Engineers need to put transparency first when designing and implementing AI-driven systems in order to address this problem. This entails defining distinct lines of accountability, explaining the decision-making process used by these systems, and improving the understandability of algorithmic processes.

Respecting the ethical norms necessary for automated decision-making requires taking an open and knowledgeable stance. It not only increases confidence in these systems but also gives engineers the ability to respond to issues promptly and efficiently. Maintaining openness contributes to upholding the public's trust and the ethical integrity of mechanical engineering by helping to strike a balance between the ethical consequences of using AI systems and their efficient operation.

Privacy concerns and risks

Artificial intelligence (AI)-driven mechanical engineering raises important privacy concerns in the age of smart and connected systems. Large volumes of data are generated and processed by these technologies, raising important questions about data ownership, consent acquisition, and protection. Privacy breaches are more likely to occur in industrial and consumer applications.

Thorough ethical examination is necessary in this case. Ensuring that privacy considerations are not just recognized but also actively included into these AI systems' operation and design is crucial. This entails putting in place strong data protection safeguards, open data handling procedures, and precise guidelines for data ownership and user consent. The objective is to maximize the advantages of AI in mechanical engineering while protecting private and sensitive data from abuse or illegal access. In the constantly changing world of smart technology, safeguarding privacy standards and preserving trust require a high level of ethical oversight. A proactive approach is necessary to mitigate privacy risks. Strong data protection techniques like anonymization and encryption must be woven into the design of AI systems by engineers (62). Furthermore, maintaining the confidence of people and organizations that depend on these networked systems requires open communication about data usage and compliance with privacy laws (62).

There are risks and unforeseen repercussions associated with integrating AI into mechanical engineering. It's critical to fully comprehend and mitigate risks, from unforeseen societal effects to safety threats brought on by malfunctioning systems. Beyond the immediate usefulness of AI-driven processes, ethical issues also take into account the wider ramifications for society and the environment.

Robust risk assessment techniques during the design and testing phases are necessary to address these problems. Engineers are required to design fail-safe procedures and foresee both intended and unforeseen consequences. Continuous observation and adjustment are essential to handle new hazards as technology develops (63).

Creating Industry Standards and Regulatory Frameworks

Without industry norms and regulations, the ethical path of AI in mechanical engineering runs the risk of becoming confusing. In order to create complete and lucid regulatory frameworks and standards that oversee the ethical aspects of artificial intelligence, engineers, legislators, and industry executives must work together (64). This entails laying out the guidelines for fair and transparent AI practices, as well as defining ethical standards and accountability procedures.

Instilling confidence among stakeholders, ranging from consumers to enterprises, regulatory frameworks not only offer a path for ethical development but also cultivate a climate of trust in AI-driven mechanical systems. By fostering a shared commitment to responsible innovation, these frameworks make sure that the industry develops within the parameters of morality. Continuous learning is necessary for mechanical engineers to stay up to date with new ethical issues and technology developments. Initiatives spanning the industry and professional development programs can be extremely helpful in promoting a culture of continuous ethical education in AI (64).

"Imparting knowledge about the ethical implications of AI-driven mechanical engineering to a wider audience requires awareness campaigns," claims Hazim Gaber (61).

This encompasses not just experts in the domain but also legislators, instructors, and members of the public. Engineers contribute to a society that is aware, watchful, and actively involved in determining the ethical course of AI in mechanical engineering by advancing a shared understanding of AI ethics. Every stage of the process, from design to compliance with regulations and continuous training, helps to build an ethical framework that guarantees the appropriate application of AI in the field.

The Prospects for AI Ethics in Mechanical Engineering

It is not just the individual's obligation to shape a responsible AI future. It demands a cooperative strategy that cuts across academic fields, business sectors, and social domains. The public, legislators, and engineers must work together to establish and maintain moral guidelines for AI-driven mechanical engineering. This cooperative strategy entails creating precise legal structures that guarantee responsibility and define moral standards (65).

Informed by awareness campaigns and educational programs, public participation plays a crucial role in keeping stakeholders accountable and guiding the development of AI in a way that is consistent with society values. In mechanical engineering, the ethical implications of AI are not limitations but rather guiding principles that show the way to a future where innovation is not only ground-breaking but also morally robust. In order to successfully navigate the complexity of AI and make sure that the future we create is both fundamentally compassionate and technologically cutting edge, engineers, legislators, and the general public must work together.

Engineer’s ally

Introduction

Background and Inspiration

I was inspired to start Engineer's Ally by something I encountered while writing my thesis on "Artificial Intelligence Supported Mechanical Engineering Design." My interest with AI's potential combined with my likeliness of mechanical engineering led me to conceive a tool that could greatly improve the engineering design process. My research showed that engineering requires a wide range of information, from intricate design standards to technology breakthroughs, and that artificial intelligence (AI) has the ability to make this process more efficient.

Conception and vision

Ideation and Purpose

The idea for Engineer's Ally crystallized while exploring the complexities of mechanical engineering for my thesis. I realized that there was a gap in the theoretical knowledge and its practical application, and I needed a tool to fill it. Thus, Engineer's Ally was designed to be an AI-powered helper that could offer mechanical engineering experts-level advice through chatting.

Development journey

Bringing this concept to life wasn't an easy task. Numerous hours were spent developing, testing, and perfecting it. The development of Engineer's Ally needed in-depth knowledge of mechanical engineering as well as AI techniques. Large volumes of technical data from prestigious engineering texts had to be integrated into the AI model in order for it to be able to access the data and use it appropriately in a variety of engineering scenarios. The step of optimization required a lot of work. With every iteration, the goal was to improve the AI's accuracy, responsiveness, and usability so that engineers of all skill levels could rely on it as a dependable and understandable tool.

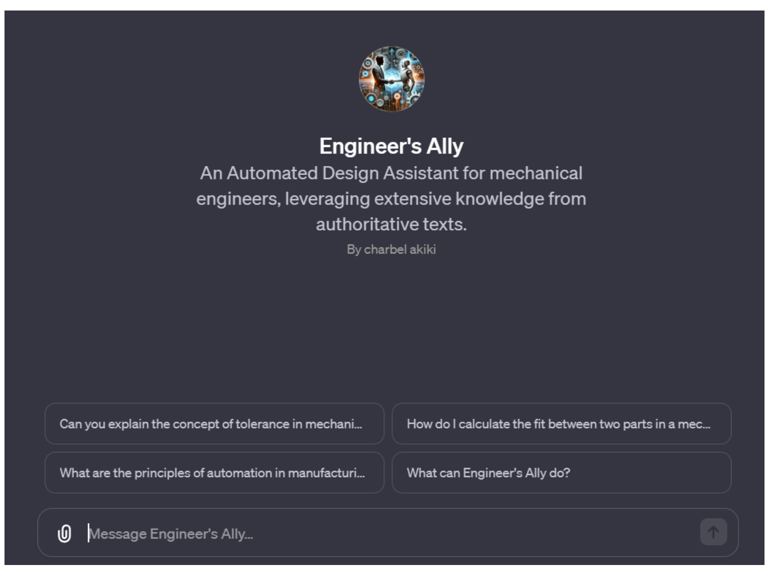

Fig. 19.: Engineer's Ally

Core features and capabilities

Expert-Level Advice and Information: Engineer's Ally helps a wide range of users, from experts to learners, by deciphering design standards, choosing materials, assisting with tolerance analysis, and many more. It facilitates quick access to specialized knowledge, which improves decision-making and research.

Application and reliability

There are several methods to make use of an engineer's ally. It can serve as a rapid reference manual for experts in need of particular information, a consultant for intricate mechanical engineering difficulties, or a tutor for novice students learning the ropes. The authoritative quality of its training materials and its capacity to uphold the norms and facts included in these documents are the main sources of its dependability. Users are encouraged to apply their judgment and knowledge, especially in circumstances that may differ from traditional practices or entail fresh ideas, even though it can provide highly informed suggestions and assessments.

Enhancement and future direction

In the future, Engineer's Ally's potential might be increased by regular updates that incorporate the most recent findings and advancements in mechanical engineering. Real-time data, market trends, and new technology could all be included to increase its applicability and efficacy. It might also become a more dynamic, hands-on engineering aid by adding interactive elements like CAD tools or simulation software, which would change it from a merely informative resource.

Potential disadvantages and considerations

Limitations in Scope and Understanding: Although Engineer's Ally has a vast knowledge base, it may not be able to cover every specialized area of mechanical engineering. Because its answers are predicated on the data it has been trained on, it might not be able to fully comprehend or offer insights into recently developing or extremely specialized aspects of the industry.

Danger of Over-Reliance: Users run the risk of being unduly dependent on Engineer's Ally for solutions, which could impair their ability to solve problems and exercise critical thought. This could impede the development of a thorough, fundamental grasp of mechanical engineering topics, particularly for students.

Human Oversight is Required: Users shouldn't just follow the AI's instructions at face value. Reviewing and evaluating its recommendations is essential given that AI, no matter how sophisticated, is still prone to mistakes and has limitations when it comes to comprehending context or the subtleties of certain technical challenges.

Inconvenience and Inaccuracy in Some Contexts: In real-time complex engineering scenarios, when human intuition and hands-on experience are crucial, Engineer's Ally may not always offer the most correct or convenient solutions.

Ethical and Intellectual Considerations: Using AI to solve engineering problems creates issues with intellectual property rights for concepts and designs. The ethical issue of AI possibly taking the place of humans in some engineering process roles is another.

Availability

Currently, Engineer’s Ally can be compared to a baby making its first steps and only accessible through a shared link where I submitted at the moment of writing among several mechanical engineering discussion forums online and awaiting approvals. This step was taken as a public testnet for the new born, reviews are awaited and lots of improvements to be made. Next step will take place after final adjustments are made and finalized where Engineer’s Ally will go public on GPTs store and be available for every Engineer seeking assistance, futuristically, a subscription-based program will be implemented for the use of the chatbot.

Feel free to try it and test it using the following link: https://chat.openai.com/g/g-bmO8sVJaa-engineer-s-ally, on a small note Engineer’s Ally can only be accessed for OpenAI, Inc. subscribers, reviews and opinions are appreciated.

Summary

A Balanced Viewpoint: Engineer's Ally is an important advancement at the nexus of mechanical engineering and artificial intelligence, but its use must be approached from a fair and impartial standpoint. To fully utilize its advantages and uphold the integrity and expertise of the engineering profession, it is imperative to acknowledge its constraints and associated hazards.

Discussion

Transition from Traditional Design to AI-Enhanced Methods

Mechanical engineering has traditionally relied on traditional design approaches, which frequently involved a methodical, sequential procedure that was time-consuming and, occasionally, constrictive in terms of creativity. This method has been completely transformed by the development of AI and machine learning, which provides more innovative, dynamic, and cost-effective solutions. Even if they were efficient, the conventional top-down and bottom-up design approaches frequently found it difficult to quickly adjust to new technology and shifting requirements. Artificial Intelligence (AI) presents a flexible substitute for these traditional techniques due to its quick data processing and pattern recognition capabilities.

Understanding AI, ML, and DL in Mechanical Engineering

In mechanical engineering, artificial intelligence (AI) is primarily utilized to automate repetitive operations, improve decision-making, and promote creative design processes. The fields of machine learning (ML) and deep learning (DL), which are branches of artificial intelligence, have revolutionized the way that designs are imagined and refined. New possibilities in design optimization and predictive maintenance have been made possible by ML's capacity to learn from data and get better over time, as well as DL's expertise in managing complicated large-scale data sets.

Current Capabilities and Software in AI-Enhanced Engineering

AI is presently used in a number of tools and applications to help engineers. These include specialist tools for material selection, stress analysis, and even environmental impact evaluations, as well as CAD and CAE software combined with AI algorithms. These technologies' incorporation of AI has improved the precision and dependability of engineering solutions in addition to streamlining the design process.

Machine Learning's Role in Design

The application of machine learning to mechanical design is especially interesting. Its capacity to examine previous ideas, draw lessons from achievements and setbacks, and recommend improvements has drastically shortened the time needed to build new goods. In generative design, where AI suggests design solutions based on predetermined restrictions and goals, ML algorithms have also been used to optimize design parameters and forecast material behaviors.

Challenges and Limitations

Although it seems promising, there are many obstacles in the way of mechanical engineering's use of AI and machine learning. Improving data quality, creating reliable data pretreatment techniques, and guaranteeing the smooth integration of AI technologies with current mechanical systems under the ethics roof are all necessary to address these problems. AI in mechanical engineering has a bright future, but overcoming these obstacles will require significant thought and planning.

Engineer’s Ally

My creation, Engineer's Ally, is the pinnacle of AI integration for mechanical engineering. It integrates the extensive body of knowledge on mechanical engineering with the analytical and predictive powers of artificial intelligence. Engineer's Ally is a companion for engineers as well as a tool, providing advice, ideas, and insights on a range of mechanical design topics. Its creation is evidence of AI's ability to close the knowledge gap between theory and practice, simplifying and enhancing the understanding of intricate engineering ideas.

Conclusion

In the realm of mechanical engineering, the transition from conventional design procedures to AI-enhanced processes represents a critical turning point. The integration of AI, ML, and DL into mechanical design has facilitated a number of procedures and unlocked novel avenues that were previously unachievable, as this thesis has shown. AI has the ability to completely change the way engineers work, learn, and develop. Examples of such tools are Engineer's Ally. In the future, artificial intelligence (AI) will play an increasingly larger role in mechanical engineering. AI technological breakthroughs will make products like Engineer's Ally even more advanced, providing engineers with more precise and intuitive support. AI-enhanced mechanical engineering offers a world where design constraints are greatly reduced, efficiency is increased, and innovation is continuously spurred.

To sum up, this thesis emphasizes how AI is revolutionizing mechanical engineering. The creation and application of Engineer's Ally are prime examples of how artificial intelligence (AI) may greatly improve mechanical engineers' skills in addition to complementing them. It will be crucial going forward to keep investigating and utilizing AI's capabilities to expand the realm of mechanical engineering possibilities.

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