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Review Article

A Review of Generative Models for 3D Vehicle Wheel Generation and Synthesis

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Abstract: Integrating deep learning methodologies is pivotal in shaping the continuous evolution of computer-aided design (CAD) and computer-aided engineering (CAE) systems. This review explores the integration of deep learning in CAD and CAE, particularly focusing on generative models for simulating 3D vehicle wheels. It highlights the challenges of traditional CAD/CAE, such as manual design and simulation limitations, and proposes deep learning, especially generative models, as a solution. The study aims to automate and enhance 3D vehicle wheel design, improve CAE simulations, predict mechanical characteristics, and optimize performance metrics. It employs deep learning architectures like variational autoencoders (VAEs), convolutional neural networks (CNNs), and generative adversarial networks (GANs) to learn from diverse 3D wheel designs and generate optimized solutions. The anticipated outcomes include more efficient design processes, improved simulation accuracy, and adaptable design solutions, facilitating the integration of deep learning models into existing CAD/CAE systems. This integration is expected to transform design and engineering practices by offering insights into the potential of these technologies.

Keywords: 3D Vehicle Wheels; Artificial Intelligence; Computer-Aided Design (CAD); Computer-Aided Engineering (CAE); Deep Learning; Generative Models.

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1. Introduction

Computer-Aided Design (CAD) and Computer-Aided Engineering (CAE) have undergone significant transformations in recent years, driven by advancements in computational capabilities and the demand for more sophisticated design solutions. Traditionally, CAD systems have relied on manual inputs and iterative processes, leading to time-intensive design workflows. Meanwhile, CAE systems face challenges in accurately simulating complex mechanical components, particularly evident in the intricate nature of 3D vehicle wheel designs. The need for efficient, automated design processes and precise simulations has prompted researchers and practitioners to explore cutting-edge technologies, with deep learning emerging as a promising frontier. Deep learning, a subset of artificial intelligence (AI) characterized by neural networks with multiple layers, has demonstrated remarkable capabilities in pattern recognition, optimization, and generative tasks. Integrating deep learning can revolutionize design methodologies and enhance simulation accuracy within the realm of CAD and CAE. The complexity of 3D vehicle wheel simulations presents a special opportunity for generative models, such as variational autoencoders (VAEs) and generative adversarial networks (GANs), which have demonstrated proficiency in automating the production of complicated designs [1]. While previous studies have explored aspects of deep learning in CAD/CAE, there is a distinct gap in the literature concerning a comprehensive review focused on implementing generative models for 3D vehicle wheel simulations. Existing methodologies often lack specificity to complex mechanical components, and a consolidated analysis of the state-of-the-art techniques, challenges, and potential solutions in this context is notably absent [2]–[6].

The dynamic evolution of technology has pushed Computer-Aided Design (CAD) and Computer-Aided Engineering (CAE) to unprecedented heights. Integrating deep learning transforms design processes. From conceptualization [7]–[10], CAD builds virtual prototypes [11], while CAE verifies performance, prompting design adjustments. Integrating CAD and CAE systems is crucial in today's collaborative design environment. The existing wheel design process faces inefficiencies and limits in concept engineering [12]–[14]. Addressing these challenges, this study introduces a deep learning-based generative design framework facilitating joint reviews by designers and engineers for detailed design advancement [15]. This project extensively explores the convergence of CAD, CAE, and deep learning, emphasizing the transformative role of generative models in simulating 3D vehicle wheels. While foundational, traditional CAD/CAE systems often encounter challenges in the intricacies of designing and simulating complex mechanical components. The manual design processes are time-consuming, and the precision required for accurate simulation, especially in the context of 3D vehicle wheels, remains a substantial hurdle. However, it is also important to harness the capabilities of deep learning, particularly emphasizing generative models. By doing so, we aspire to not only revolutionize the design processes but also redefine the parameters for accurate and efficient CAE simulations [7], [16], [17]. Simultaneously, our research endeavors to augment CAE simulations, utilizing deep learning techniques to predict mechanical properties and optimize performance metrics tailored explicitly for 3D vehicle wheels. The utilized approach explores several deep learning architectures, including convolutional neural networks, variational autoencoders (VAEs), and generative adversarial networks (GANs) (CNNs). Empowering these models involves training on extensive datasets featuring varied 3D wheel designs paired with corresponding simulation data. This ensures models learn from diverse designs, proficiently generating optimized solutions. Beyond academic achievements, our expectations encompass a streamlined generative design process, heightened simulation accuracy, and the creation of adaptable design solutions for diverse optimization goals. Our commitment extends to practically integrating these advancements into existing CAD/CAE systems, bridging the theoretical-innovation-real-world-engineering gap.

This review's limitation in/out-sight may not encompass every aspect of generative models or 3D vehicle wheel design due to time and resource constraints, certain methodologies, applications, or emerging technologies [14], [17]. The quality and availability of data sources may impact the depth and reliability or work, limited access to certain datasets or discrepancies in data quality could affect the generalizability of findings for CAD/CAE systems, the rapidly evolving nature of generative modeling techniques and 3D design technologies means that new methodologies or advancements may have emerged since the completion of this review. [18] While the integration of generative models in 3D vehicle wheel design holds promise, practical implementation may encounter various challenges, such as technical constraints, compatibility issues with existing design software, or limitations in computational resources required for complex modeling tasks[19], [20]. Various reviews and research have been done, and despite efforts to maintain objectivity, reviewer biases or subjective interpretations may influence the analysis and synthesis of research findings. Additionally, the selection of studies or methodologies included in the review may introduce inherent biases based on the reviewers' perspectives or preferences. In essence, this review review seeks to illuminate the current landscape of CAD/CAE systems in the following; To contribute not only to the academic discourse but also to the broader realms of design and engineering, ushering in a new era of efficiency, innovation, and precision in the realm of complex mechanical design and simulation. Exploring the integration of deep learning into traditional CAD/CAE system, and specifically, the transformative potential of generative models in the simulation of 3D vehicle wheels. Also, to bridge this gap, an in-depth examination of how deep learning, and specifically generative models, can be harnessed to propel advancements in CAD/CAE systems will be conducted, with a specialized focus on 3D vehicle wheel simulations. A potential limitation of the research topic could be the lack of publicly available datasets for training and evaluating generative models. While there are a number of publicly available datasets for 3D object generation, there may not be enough specifically designed for vehicle wheels. In addition, the diversity of vehicle wheels may make it difficult to create a dataset that is representative of the real world. This could limit the ability to generate realistic 3D vehicle wheels that represent the diversity seen in the real world.

This research is organized as follows: Section 2 presents Computer-Aided Design (CAD) and deep learning. Section 3 presents describes the overview of CAD/CAE. Section 4 presents the 3D vehicle wheel under real-world conditions with deep learning, and Section 5 concludes the future work of the study.

2. Computer-Aided Design (CAD) and Deep Learning

2.1. Generative Designs

Generative design is an AI-based product design method using algorithms to produce many design alternatives depending on a set of input parameters [21], [22]. This approach can be particularly useful in the design of complex 3D models such as wheels. For example, researchers at the University of Illinois developed an AI-based generative design system for automotive wheels. This system used a combination of genetic algorithms and finite element analysis to generate optimized designs that met specific performance criteria. Study [23] is credited with starting generative design research in the early 1970s. According the 1970s saw the development of design algorithms that mimicked nature. Significant research delved into generative models after the introduction of parametric CAD tools in 1989. Beyond research, generative design applies to various manufacturing sectors, including automotive, aerospace, and construction. The ultimate aim of generative design has been outlined in a number of studies, with a focus on creating spatially inventive, practical, and efficient techniques using existing manufacturing and computational capabilities. According to [24], the primary objective of generative design is to expand the design space. During the conceptual design stage, generative design may present initial designs that designers hadn't considered, offering fresh inspiration [11].

In essence, generative design refers to any computational model employed for design investigation. Described as a designer-inspired, parameter-constrained design exploration process, it operates atop background-based parameterized drafting programs tailored to facilitate design as an evolving process. Through the parametric representation of design morphology and result screening, we can condense a vast design space into more manageable sectors, incorporating limitations such as geometric viability, manufacturing capabilities, cost, and performance considerations [11], [15]. Swarm artificial intelligence, form grammars, L-systems, evolutionary algorithms, and cellular automated systems are a few study methodologies. Generative design is described as the automatic investigation of design under predetermined restrictions. Generative design can present preliminary designs throughout the conceptual design stage, providing new ideas. Conventional generative design uses exploratory methods to manage feasible shape changes through parametric control and produces a large number of designs using genetic algorithms (GAs).

2.2 Generative Models for 3D Vehicle Wheels

In this study, GANs are applied to generate 3D models of vehicle wheels [25]. Trained on extensive datasets of existing wheel designs, the models acquire intricate details and styles unique to different wheel types. The generative model then produces entirely new, customized wheel designs while complying with industry standards and safety regulations [26]. Building on the findings from the study [27], for design exploration, integrated topology optimization yielded a new design comparable to the reference, overcoming low compliance through topology optimization applied to an older design (the connection). Research [3] suggested using boundary equivalent GAN learning for iterative design exploration to develop a new reference design. In contrast to studies using bracket designs, this approach excels in generating authentic product designs from a reference design, as demonstrated in the design of vehicle wheels. To extend the 3D wheel CAD/computer-aided engineering process for industrial applications [28] built upon the work of [20]. Study [28] succinctly articulates the concept of exploring diverse designs through topology optimization. The initial step involves searching for other local optima for the same issue, utilizing different starting designs, optimizers, and filtering techniques [29], [30]. While the industry rebrands topology optimization as "generative design" and provides CAD tools employing it for design exploration, deep learning is currently lacking in its incorporation into these tools. Ongoing research is exploring the potential of deep learning to enhance the performance of topology optimization-based generative design in design exploration [15], [28], [31]. Studies [32], [33] employed convolution filters of deep belief networks and reduced-order models to generate various topology designs. In research [34], proposed generative design based on reinforcement learning eliminates the need for preoptimized topological iteration.

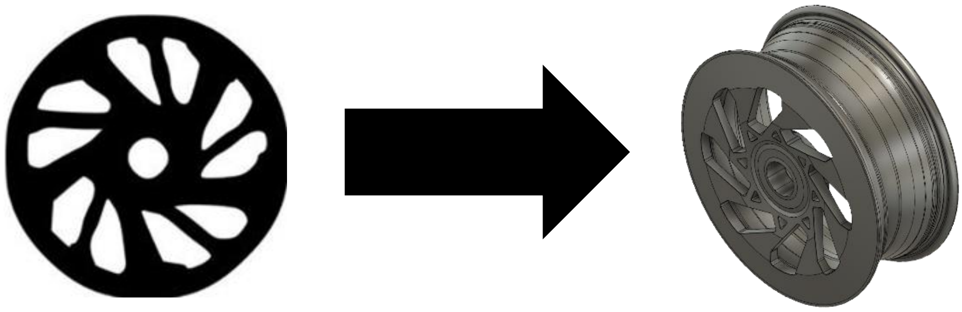

Figure 1. Data (Image) Processing of Rim to 3D Vehicle Wheel

2.3 Generative Models for 3D Vehicle Wheels

Generative design algorithms optimize structures by iteratively removing material that is not structurally necessary, resulting in lightweight yet robust designs. The approach in [26] aligns to reduce the weight of electric vehicles (EVs) to improve energy efficiency. Reducing the weight of vehicles is crucial to increasing efficiency. With the rise of electric vehicles that must balance heavy battery systems while achieving useful range, this has become even sharper focus [16]. One method is through a technique known as lightweighting. Lightweighting reduces the overall weight of different parts by using design [35], [36]. Generative design is a relatively new approach that sees engineers input design [9] goals such as lightweight into the software and other parameters such as manufacturing methods and performance requirements [37]. Unlike other design methods, generative design does not require a starting geometry. The users input the areas that the part must keep and identify which areas that material should not enter [4]. Then the performance requirements are inputted; these can include constrained areas, forces, and pressures on the part, etc.). Following this, other inputs can be added, such as the possible materials and any manufacturing restraint, such as minimum wall thickness or the drill bit size for CNC, etc. [24], [32]. The result of each pass is the entry point for the next iteration. Each step is available for the designer to view, and they can modify the constraints to direct the evolution of the design [23]. At the end of the generative design, they can compare several solutions and decide which one to pursue. A significant difference of generative design is that designers can start the process with relatively lean resources. Computations are fast and can significantly influence real-time cutting design process times [38].

3. Computer-Aided Engineering (CAE) and Deep Learning

Despite being a well-established technology for over 50 years, computer-aided engineering is still largely applied in the early stages of product design. It does not have a smooth integration across other phases. This paper delves into the application of artificial intelligence (AI) and machine learning (ML) in virtual manufacturing and computer-aided engineering (CAE), with a focus on deep learning (DL) models and their potential to drastically shorten simulation lifecycles in a variety of markets. The democratization of AI/DL for all design engineers utilizing CAE necessitates addressing critical success aspects, even as we anticipate a sharp increase in deploying these approaches in the years to come. Furthermore, it could act as a link between data silos in the actual and virtual worlds of contemporary manufacturing, production, and product creation. [17].

3.1. Computer-Aided Engineering (CAE) Automation

CAE simulation results utilizing the 3D CAD files acquired for the 3D Wheel model. This involves using a CAE tool to simulate the vehicle's behavior under various conditions. In this work, the modal estimation determined the normal frequency of the lateral feature; the outcomes were preserved as information with labels that could be utilized for deep learning. [39] which was used to perform the CAE. [18], [40]–[43].

3.2. Computer-Aided Engineering (CAE) and Deep Learning Integration

Topology optimization has been explored through various data-driven approaches facilitated by machine learning. Examples include K-means [44]–[46], Support Vector Machine (SVM) [12], [21], principal component analysis (PCA) [47]–[49], Gaussian process [4], [8], neural networks [38], [50]–[52], and random forests [10], [53]–[55], which have been applied in these methodologies. Another study by [12], [49], [56] proposed a generative design approach for the optimization of lattice structures in 3D printing. The approach used a combination of CNNs and reinforcement learning to generate lattice structures that met specific strength, stiffness, and weight requirements. The study showed that using deep learning in generative design can improve the performance of 3D objects while reducing the need for manual allowance in the design procedure. AI exhibits remarkable flexibility in adapting to changes in viewpoint, facilitated by the visual cortex supporting 3D structure perception [57]. Conversely, many computer vision models, learning visual representation from 2D image pools, struggle to generalize across novel camera viewpoints. A recent shift in vision architectures embraces convolution-free structures like visual Transformers, operating on tokens derived from image patches. However, as in convolutions, these Transformers lack explicit operations for learning viewpoint-agnostic representation. Introducing a 3D Token Representation Layer (3DTRL) addresses this by estimating 3D positional information and leveraging it for viewpoint-agnostic representations. Key components include a pseudo-depth estimator and a learned camera matrix for geometric transformations on tokens, allowing 3DTRL to recover 3D positional information from 2D patches. Easily integrated into a Transformer [15], [58]–[62] in practice. In the context of 3D conceptual wheels, several studies have explored and enhanced generative design techniques to refine the concept and evaluation of wheels. One study by [55] introduces a generative approach for designing and optimizing vehicle wheel structures using a combination of CNNs and genetic algorithms. Applied to a racing wheel design, it generated diverse designs meeting predefined criteria for weight, stiffness, and aerodynamics. The study demonstrates that generative design techniques significantly enhance the efficiency and effectiveness of the wheel design process [63], [64].

Research [47] introduced a generative design approach aiming to optimize wheel geometry by combining Generative Adversarial Networks (GANs) and reinforcement learning. Applied to a mountain bike wheel design, the approach successfully generated designs meeting predefined criteria for strength, stiffness, and weight. The study demonstrated that implementing generative design techniques can enhance wheel performance while minimizing the need for manual intervention in the design process. According to [18], the success of autonomous vehicles, positioned as the future of transportation solutions, relies heavily on reliable perception. Image processing and sensor fusion approaches are thoroughly reviewed in this review paper to guarantee vehicle efficiency and safety. This study examines issues in computer vision and machine learning approaches for object identification, recognition, tracking, and scene comprehension. These include the need for real-time processing, robustness in inclement weather, and the integration of complicated sensor data.

Knowledge transfer, autoencoder, and convolutional neural networks (CNN) are the three main deep learning techniques included in the suggested design. CNN-based object detection techniques have drawn a lot of interest because of the tremendous improvements that CNNs have made in vision-based applications, especially in traffic monitoring. The remarkable real-time multi-object identification capability of methods like You Only Look Once (YOLO) and its variations have gained popularity in high-resolution traffic surveillance settings. [65]. Deep neural networks (DNN) featuring CNNs are widely employed for constructing concept models in engineering issues, utilizing supervised learning methodologies. CNNs, known for their exceptional ability to detect patterns and shapes, find extensive application in sectors where computer vision is pivotal [66]. Convolutional and pooling layers are combined in the CNN design, and fully connected layers are built on top. This design served as the basis for a model. [32]. To distinguish between different models used for different tasks, Convolutional Neural Networks (CNNs) are vital. With hierarchical data features, CNNs' basic architecture emulates human visual processing abilities, allowing them to recognize, classify, and interpret environmental information [18]. Deep neural networks (DNNs) are commonly utilized for dimensionality reduction in unsupervised learning [33]. With the same sizes for the input and output layers in the autoencoder architecture, autoencoders, in particular, compress high-dimensional input data into a low-dimensional latent space. When input data is compressed using encoders, decoders restore the latent space to the output data. To achieve dimensionality reduction of Computer-Aided Design (CAD) data, we implemented a convolutional autoencoder comprising only convolutional and pooling layers [32], [56]. In simulation-based design optimization algorithms, high-quality polygonal meshes are often required to represent designs. Unevenly distributed 3D point clouds are difficult to mesh because it's an ill-posed problem that will usually require human adjustment and validation. Researchers have recently used deep neural networks to tackle the mesh rebuilding task (DNNs).

3.3. CAD/CAE- Centric

A CAD-centric or CAE-centric mechanism can be used to integrate computer-aided engineering (CAE) and design (CAD), especially when geometric model optimization is required. [23]. Still, most recent studies have focused mostly on CAD-centric methodologies. The schematic illustration of the CAD-centric and CAE-centric methods, each with a different foundation for interaction with CAD/CAE systems, is shown in Figure 2.

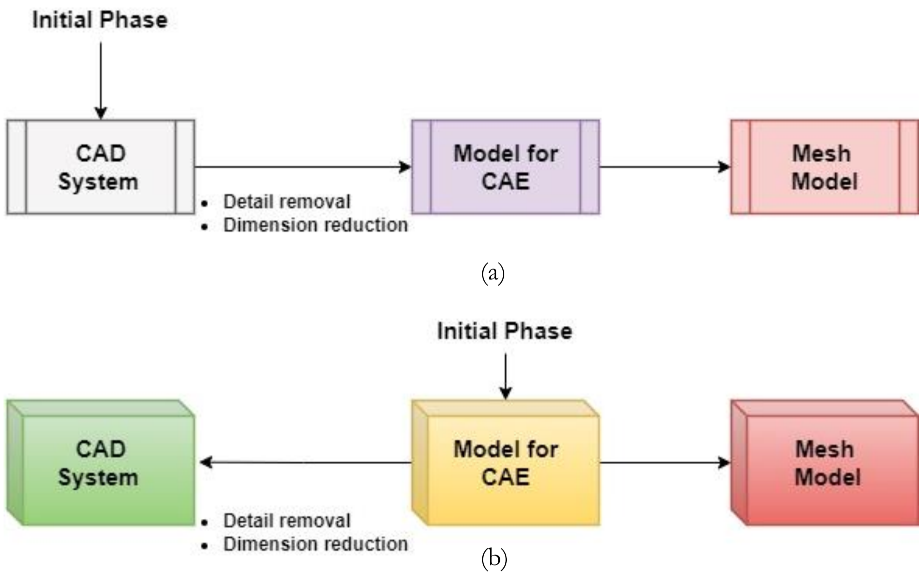

Figure 2. (a) Streamlined CAD-Centric Integration Approach for Linking CAD to CAE (b) Streamlined CAE-Centric Integration Approach for Linking CAD to CAE

The CAD system is the starting point for the CAD-centric approach, which reduces dimensionality and simplifies detailed CAD models to make them easier for a CAE system to analyze. Study [65] presented an integrated platform that combines CAD and CAE and features a Graphical User Interface (GUI) for visualization. Using an integrated environment to optimize the design of an automotive engine cylinder, this method starts with the virtual prototype generated by the CAD system [67]. Research [32] created an injection molding design support Knowledge Base (KB) system centered around CAD for plastic items. Research [30] intended to combine CAD and CAE for high-speed design and manufacturing, with an analytical system acting as the finish system. Studies [37], [68]–[71] developed an integrated platform that connects CAD and CAE and optimizes the geometric structure of machine tools by using a closed-loop pattern from the CAD system. Research [37] created a closed-loop framework that works from the CAD to the CAE systems. Study [15] created a framework for CAD-based integration that combines Design for Cost and CAE systems to optimize product models. [66] designed a gas turbine flow path using an integrated platform for structural optimization that is CAD-centric and integrates with a CAE system. Studies [68], [72] developed an integrated gas turbine component design platform that unites CAD and CAE. Model optimization is done using the CAE system after CAD-based parametric modeling.

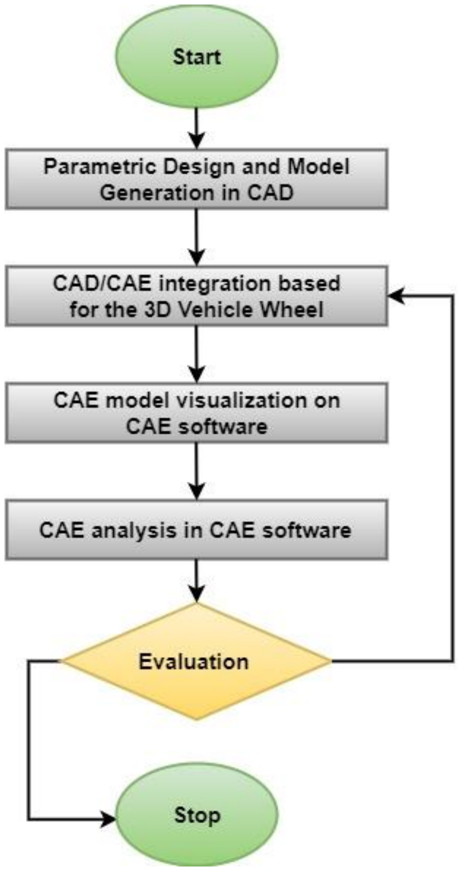

Figure 3. Flowchart of Closed-loop operational process.

The foundational design model, which is mostly examined in the CAE system, is where the CAE-centric method begins. The CAE system then uses information and measurements from the basic design model to forecast the geometry of the product model. After that, the CAD system displays this improved model. Studies [9], [38], [73] provide an integrated system that combines CAD and CAE with the goal of optimizing product model geometry through analysis using the Finite Element Method (FEM). This method starts with a model for CAE analysis and ends up with an optimization result for CAD geometry. A comparable emphasis is seen in the study conducted by [43], in which a CAE-centric approach optimizes the plastic molding process's shape. Study [74], [75] developed a CAD-to-CAE integrated platform focusing on CAE to enhance vehicle structural design. Studies [23], [59], [76], [77] provide a neutral, feedback-controlled file-based CAD - CAE integration platform that optimizes geometric design variables based on feedback from CAE analyses. Studies [24], [64], [77][78] support a CAD to CAE digital framework that is focused on CAE to optimize a 5-DOF robot joint's design.

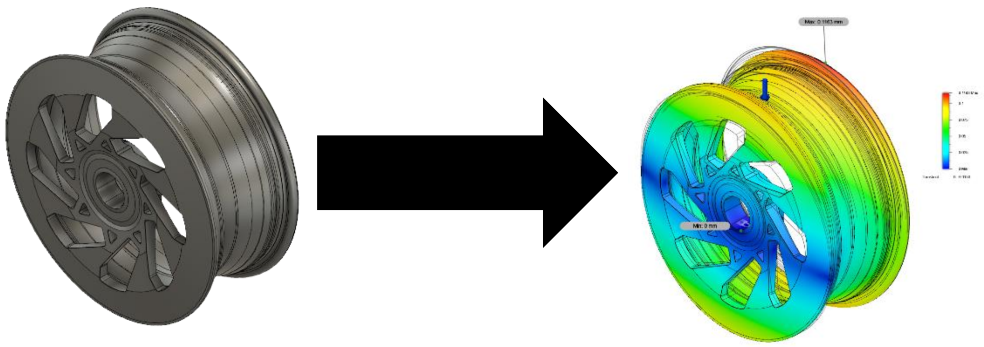

Figure 4. CAD/CAE-Centered

3.4 CAD/CAE Deep Learning

Artificial intelligence (AIdeep)'s learning subset, which uses complex neural network architectures to extract insights from large amounts of data, has proven incredibly effective in various fields. Deep learning applications for computer-aided design (CAD) and computer-aided engineering (CAE), crucial processes in new product creation, have garnered attention recently. Studies [31], [49], [52], [60] integrating deep learning with CAD/CAE is more practical than other engineering domains because CAD data has been used in many deep learning research for tasks like segmentation and classification [46], and the development of metamodels in CAE research has long depended on machine learning [20]. During the conceptual design stage, a metamodel or surrogate model is essential for quickly evaluating the engineering performance of multiple design contenders. Deep learning's capacity to accurately imitate high-dimensional and nonlinear physics makes it a powerful tool for surrogate modeling in CAE research [65], [72] [79]. To effectively use deep learning, engineers must first generate a set of CAD models and compile CAE findings, which presents a considerable hurdle.

Generative design holds the potential to address the problem of scarce data availability. Within the designer's given limits, designs are independently explored using this computational design process [14], [18], [28], [80], [81]. Recent generative design research combines deep learning and topology optimization to navigate large design areas efficiently [13], [82], [83]. Expanding on the foundation created by [46] to address the 3D wheel design complexity in industrial applications, our research on 2D wheel design further extends the deep learning-based generative design approach, demonstrating its usefulness in the automobile industry. Using cutting-edge technologies specifically designed for the conceptual design stage, generative design and CAD/CAE automation are all smoothly integrated into the suggested CAD/CAE framework, powered by deep learning. By using deep learning to automate the creation and assessment of 3D CAD data, this approach helps to find workable conceptual concepts early in the design process.

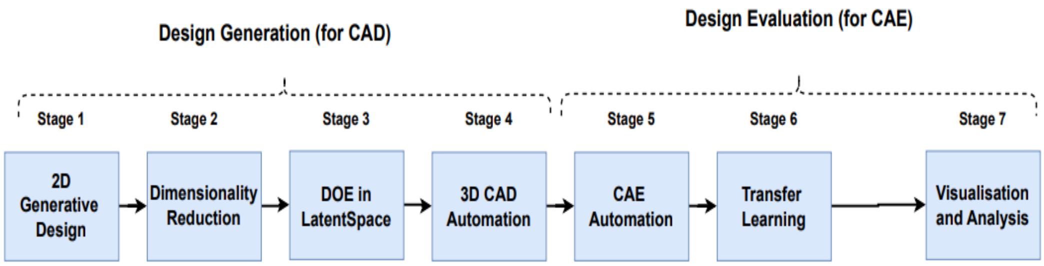

Figure 5. Deep CAD/CAE Workflows

3.5 CAD/CAE Reinforce Learning

Reinforcement learning (RL) is a machine learning type that involves evaluating an agent to make a conclusion based on trial and error in an environment. In the context of CAD/CAE systems, RL can be used to optimize the design of 3D objects based on predefined objectives. Some previous studies have explored the application of RL in CAD/CAE systems, including the design of car components(wheels), airplane wings, and buildings [63]. One study by [84] provides a reinforcement learning-based strategy for modeling airfoils using a CAD/CAE system. The method involved training an agent to generate airfoils based on the objectives of lift and drag coefficients. The study found that the RL-based method effectively generated airfoils that met the specified objectives and outperformed traditional optimization methods. Another study by [34], [47], [85] introduced an RL-based method for the design of truss mechanics using a CAD/CAE system. The method involved training an agent to generate structurally sound truss structures with low mass [2]. The study found that the RL-based method effectively generated truss structures that met both objectives and outperformed traditional optimization methods. As for the findings of [31], a generative design method rooted in deep learning was developed for 2D wheel design. The primary objective of this research is to broaden the applicability of the generative design method to address the 3D wheel design challenges in industrial settings, showcasing its viability within the automotive industry [86]. This study presents an efficient deep learning-based CAD/CAE system that includes advanced technologies, generative design, and CAD/CAE automation. Specifically designed for the conceptual design stage, the suggested framework uses deep learning to automate the creation and assessment of 3D CAD data. Its main goal is finding workable conceptual concepts early in the design process [3], [87].

Although RL has demonstrated potential in optimizing the design of 3D objects within CAD/CAE systems [54], [63], there are persistent challenges to address, including the substantial computational cost and the necessity for a well-defined reward function. The issue of Scan-to-CAD in CAD models, as highlighted by [57], entails extracting specific B-Rep characteristics from the matching 3D scan or figuring out the design background that made it possible. Despite recent progress, this problem is still difficult to solve, especially in practical settings where oversimplified assumptions limit the applicability of current solutions.

3.6 CAE Reinforcement Learning

In the domain of automotive engineering, the infusion of deep learning-based algorithms into CAE marks a transformative shift. Deep learning, a subset of artificial intelligence (AI), renowned for its prowess in image and data analysis, natural language processing, and pattern recognition, holds the potential to revolutionize CAE practices [33], [57]. Extending these capabilities to the specific domain of CAE, especially in simulating 3D vehicle wheels, promises unparalleled accuracy and efficiency. Manufacturers must implement strong systems-design procedures that can successfully negotiate the complexities of creating multidisciplinary systems in order to meet the demands of expediting product releases and minimizing costs. At the heart of this development process lies the utilization of high-fidelity virtual prototypes, often referred to as 'Digital Twins' [14]. While challenges undoubtedly exist, contemporary AI models stand ready to surmount obstacles encountered over the past decade. By establishing a seamless 'digital thread' throughout a product's lifecycle and incorporating feedback loops, these models enhance cost-effectiveness and elevate productivity and innovation, validated through real-world experiences to embed inherent quality [88].

This study endeavors to delve into and propel the incorporation of deep learning into CAE systems for the modeling and simulation of 3D vehicle wheels within authentic environments. [22] The objective is to generate a framework automating the creation of 3D CAD models by utilizing the capabilities of deep neural networks, such as convolutional neural networks (CNNs) and generative adversarial networks (GANs). Simultaneously, the framework aims to predict intricate CAE results accurately, elucidating the underlying engineering performance. To underpin this research, we draw insights from existing literature that explores the fusion of deep learning and CAE. Notable contributions from [28] highlight the viability of this method, which is highlighted by the proposal of a deep learning-based CAD/CAE framework for 3D conceptual design and studies investigating the effects of deep learning in CAE. Furthermore, recent strides in deep learning techniques and the advent of AI in CAE simulations validate the significance and timeliness of this research [81].

4. 3D Vehicle Wheel Under Real World Condition with Deep Learning

Accurately identifying surrounding objects is a fundamental component in developing automobile wheels. Neural networks, artificial intelligence-powered algorithms that classify data in ways reminiscent of human cognitive processes, are often used for this task [14], [16], [35], [89]. To categorize data, a deep learning neural network must be trained using a specific training set, in which inputs and corresponding intended outputs are coupled [71]. The neural network may learn and classify data accurately as inputs and outputs correlate over time. The performance of the deep learning neural network is then evaluated using a different dataset, referred to as the validation set, in order to avoid overfitting during training. During training, a testing set is also kept aside to assess the neural network's accuracy on unobserved data. The Deep Learning Convolutional Neural Network is a popular type of neural network used in autonomous cars (DLCNN). Distinct regions within an image are given weights by this network, which indicates the relative importance of various visual components. Using these weights, the neural network skillfully categorizes the image according to its unique qualities [90]. To improve the model's capacity to identify adjacent items, proprietary augmentation methods are developed. One of the research projects is to create a specific dataset that serves as the testing crucible. The recommended network design is quite similar to the R-CNN (area-based Convolutional Neural Network) architecture, with a major focus on delineating the area of interest. Augmentation methods include lighting, brightness control, and regular picture improvement for the best possible clarity. [91]. While the reported accuracy in controlled

Table 1. Overview of the image processing methods explored in the scholarly works.

Computational Procedures	Narrative portrayal	Strengths	Limitations
YOLO DNN and CNN [14], [27], [81]	Predictive bounding boxes for objects are produced using the YOLO (you only look once) CNN, which divides an image into grid cells. ▪ 24 convolutional layers, 4 max-pooling layers, and 2 fully linked layers are included in this structure.	▪ Achieves a high frame rate, reaching up to 185 frames per second. ▪ Avoids the utilization of region proposals, enabling a comprehensive view of the image context and eliminating the confusion between the image background and foreground objects.	▪ Frequently encounters errors because of its architecture, which involves looking at the entire image simultaneously. ▪ Encounters challenges when dealing with small objects and those in close proximity.
Fast R-CNN [92], [52]	▪ Generates regions of interest by employing region proposals, which are indicative of potential object locations. ▪ pools the features from the proposal and applies neural network layers for classification	▪ Has high accuracy comparatively ▪ Reasonably efficient ▪ End-to-end; meaning that the network learns with more data being ran	▪ Requires an extensive, annotated training dataset. ▪ Expensive in comparison to other models
Alex-Net [83], [18]	Conventional convolutional neural network ▪ consisting of three fully linked layers and five convolutional layers. ▪ 3 Max pooling layers (occurs after 1st, 2nd, and 5th convolution layer) ▪ Backpropagation and Principal Component Analysis are used.	▪ Uses many methods such as pooling, dropout, ReLU activation	▪ Not as complex as YOLO CNN, so results are not as good. ▪ Uses 5x5 convolution filters, which are not very common today
LSTM-CNN [13], [93]	▪ Long Short-Term Memory (LSTM) CNNs work similarly to regular CNNs. ▪ Incorporate an extra layer, the LSTM layer, to grasp the overall patterns within the data.	▪ Well-suited for video recognition, which is essential in autonomous vehicles. ▪ Extremely powerful and flexible and generates good results	▪ Extremely computationally expensive due to the new layer ▪ Demands substantial memory and poses challenges for execution on typical computers.
ERFNet [57], [77]	▪ Incorporates "residual layers," enabling the flow of memory throughout the entire network across all layers. ▪ Combining feature maps (2D point clouds) to get the desired result. ▪ 23 total layers	▪ Has similar accuracy to other high-accuracy models. ▪ Executes at a faster pace compared to the majority of models.	▪ Relatively demanding in terms of computational resources owing to the presence of residual layers.
Simple-Net [88], [55], [64], [92], [94], [95]	▪ Architecture is an elementary version of a typical CNN. ▪ Contains one fully connected layer, two max-pooling layers, and only two convolutional layers.	▪ Runs fast, which was the initial goal of the study. ▪ Does not require much computing power.	▪ The architecture is straightforward, so it does not work very well. ▪ Cannot be used in practice.

environments is acceptable, the contextual coherence of the dataset fails to validate the model's usefulness in real-world circumstances. The many image processing methods used in autonomous driving are briefly described in Table 1, along with their advantages and disadvantages.

Convolutional Neural Networks (CNNs) are fundamental to autonomous vehicle navigation since they support a wide range of models for different applications. CNNs' fundamental design is modeled after human visual processing, which uses hierarchical data characteristics for perception, classification, and assimilation of its surroundings. The input layer, where raw data, including photos, enters the network, is where it all begins. These 2D-pixel arrays are evaluated using chromatic characteristics and luminosity [21], [31]. Next, we get to the convolutional layer, the network's core. It navigates across picture segments using tiny filters called kernels and computes dot products based on chromatic information and weights. To create a new cartographic representation, this procedure is applied consistently throughout the image (123 Generative Design and Topology Optimization Place in Product Development Process, n.d.) [10], [11], [18], [55]. The network configuration determines the number of convolutional layers and filter types [49], [84]. The ReLU activation function is then used, which adds nonlinearity and improves the network's capacity to recognize complex patterns. Although some CNNs do not include the ReLU activation, doing so usually increases accuracy [92]. Following activation, data moves on to the pooling layer, which is frequently the max-pooling layer designed to minimize feature map dimensions without sacrificing important information. By reducing the dimensionality, the network's resistance to disturbances and computing overhead are reduced, leading to improved sustained accuracy. Models differ in how frequently the max-pooling layer is integrated. The picture then passes through completely connected layers, where the crucial classification process occurs. Final predictions are derived from input features from earlier phases, offering a probabilistic gauge of correctness. Most neural networks need a large amount of training data to become proficient in classifying images. Gradually, however, patterns become apparent, which increases the network's classification performance.

Autonomous vehicles rely heavily on LIDAR sensors for object detection. These sensors provide detailed maps of the environment around the vehicle and enable successful object detection at night and in poor light. Utilizing laser technology, these sensors pulse forth light, which is subsequently reflected back to the sensor[50], [65], [96]. The generated data makes reliable data collecting possible, which makes it possible to create three-dimensional (3D) maps. While two-dimensional (2D) maps can be produced using older techniques, technological developments have made these less popular [36]. An Inertial Measurement Unit (IMU) is typically integrated into the system when using LIDAR sensors. The IMU helps the LIDAR sensor gather accurate data by measuring angle, velocity, and acceleration changes. When combined with a LIDAR sensor, an IMU's three accelerometers and three gyroscopes enable the measurement of crucial variables such as angular rotation, kinetic energy, and range. [1], [14]. Velodyne LIDAR is a well-liked option among the different LIDAR sensors in autonomous cars because of its demonstrated efficacy [68], [79], [97]. Since LIDAR sensors operate at higher frequencies than other sensors like radar, their superior accuracy and efficiency in determining distances are the reason for their widespread use. It's crucial to remember, though, that LIDARs cannot always measure data effectively in bad weather, which has led to research into other sensor systems like radars and webcams [83]. Another popular associated with conducting used in autonomous vehicles is radar, often known as radio detection and ranging. Radar sensors, in contrast to LIDAR sensors, collect data by examining the reflections of electromagnetic waves rather than lasers.

Conversely, cameras are essential to autonomous driving systems, mostly used for object detection. Neural networks are commonly used in conjunction with these cameras to enable object detection through machine learning methods. Neural networks learn to recognize patterns in images, improving their capacity to detect objects more efficiently [81], [98]. Moreover, image segmentation methods which split an image into distinct "regions" for separate analysis are often used in object detection to achieve better outcomes. The neural network may evaluate fewer image elements by employing picture segmentation, sometimes called semantic segmentation, which expedites analysis by reducing computational processing time [19]. Although cameras provide a significant precision level, they have recognized limitations. First, cameras have trouble performing well in bad weather, affecting their dependability and functionality in difficult climatic circumstances. In some situations, object detection may be hampered by cameras' inherent difficulties when attempting to capture a complete 360-degree field of view. There may be issues if autonomous cars only use cameras as their primary sensing technology for object recognition [19], [41]. It is clear that every detection technique covered has a unique set of drawbacks and difficulties. As such, overall effectiveness is improved over single-sensor systems by utilizing the capabilities of multiple sensors through the integration of sensor fusion techniques. Utilizing information from many sensors—including cameras, radar, and LIDAR—sensor fusion creates a point cloud, a detailed representation of the surrounding area. This strategy works well because different sensor types have different strengths and weaknesses. For example, different sensor types may detect different colors, have different ranges, and have different data quality levels. Autonomous vehicles' performance has improved because of the integration of these sensors [18]. Software methods that combine input from many sensors to create a logical and intelligible representation that the autonomous car can use in its operations are known as sensor fusion techniques.

Neural network usage in autonomous vehicles has attracted a lot of attention, which has increased in research projects using this approach. A notable instance is exemplified by the study conducted by [18], whereby object identification in autonomous vehicles was accomplished using a Radar Region Proposal Network (RRPN). Utilizing radar sensors, this approach collects information about the environment around the vehicle and creates Regions of Interest (RoI) that identify important regions within the picture. When applied with a fair degree of accuracy, radar turns out to be a more affordable option than techniques such as LiDAR. Based on the regions that have been identified, the neural network analyzes the visual input and generates predictions for object detection. Although the obtained results are better than those of Selective Search, a segmentation-based technique frequently used for object detection, they are still not optimized. Hence, the practical implementation of this strategy in real-life situations is only possible with further improvements. Simple neural networks and more complex designs are used in image-processing tasks for autonomous cars. For example, [81] the used methods include region suggestions, as previously mentioned, in conjunction with Scale-Invariant Feature Transform (SIFT) descriptors. SIFT descriptors include constructing three-dimensional models of the environment to detect and locate distinct points within a picture. Subsequently, these points are converted into numerical values and used to create a histogram using the identified characteristics. SIFT descriptors are very useful for quickly identifying crucial elements in a picture. Yet another effort undertaken by [59], [62], [99] targeted efficient object identification using a network termed Simple-Net. While this study succeeded in obtaining quicker processing speeds (0.098 s/image) compared to competitors like Fast R-CNN (which took over 0.35 s/image), its efficacy was very restricted, leaving it unfeasible for real-life applications.

The research undertaken by [39], [53] highlights the application of deep learning neural networks in traffic sign categorization. The study adopts a YOLO-CNN (You Only Look Once Convolutional Neural Network) model, having extra layers compared to a regular neural network. Training the model comprises a database built by a ZED stereo camera system, comprising two closely located cameras that collect images for evaluation. This arrangement emulates the human visual system, exploiting the disparity between views to interpret depth information in a 3D point cloud. Integrating this camera array with LiDAR and IMU sensors adds to comprehensive data gathering for framework development. Reported findings suggest a promising accuracy of 98.98% for this model. Although the architecture of the YOLO-CNN and Simple-Net models is identical, the YOLO-CNN model achieves better accuracy than Simple-Net because it has more layers and a different camera arrangement. Although Simple-Net has fewer layers than the YOLO-CNN model, it performs less accurately and has slower processing speeds. Identifying surface defects in car wheels is challenging because of the wide variety of fault types and complicated backgrounds. A YOLOv5-based algorithm for automobile tire surface defect identification is offered to solve this problem. The technique uses a self-created dataset with four different kinds of defects (linear, dotted, sludge, and pinhole) to train and test the YOLOv5s model. According to experimental data, the deep learning network achieves an average accuracy of 81.7% and 55.15 FPS [27]. Simple-Net provides shorter processing speeds, whereas YOLO-CNN delivers excellent accuracy. Each model has its benefits. An additional use of neural networks in image processing is the combination of LiDAR and camera sensors, as shown by the study by [18].

Using sensor data processed by a neural network, this research attempts to predict a car's speed. Three sensors are mounted on the automobile as part of the network architecture for end-to-end driving, where the input image—typically from a front-facing camera—influences the vehicle's movements. Support Vector Machines (SVM) and Long Short-Term Memory (LSTM) are used for these tasks. SVMs function as a classification algorithm, classifying data points by identifying a separating "line" or "plane" on a graph. On the other hand, LSTM, a kind of neural network with more memory, works well for sequentially storing data, especially when dealing with bigger datasets. By employing LiDAR and video sensors while driving on roadways, the researchers created a dataset that included over 180,000 frames. The gap rate is used to assess the algorithm's efficacy; generally, the findings show promise. Similarly, [100] LiDAR and cameras may be used to detect objects. The research emphasizes that while cameras perform well in some scenarios, more in-depth information about adjacent objects is required. As a result, an amalgamation of LiDAR and RGB sensors is used for object identification. LiDAR data and the Camera RGB picture are used for initial object identification. The items are then clipped for input into the neural network[13]. Another popular neural network design, Alex-Net, is used in data processing, and categorization is carried out. Principal Component processing (PCA) accomplishes data processing and summarization, and backpropagation automatically modifies neural network parameters for improved accuracy. However, with its obtained accuracy of just 66%, the model is inadequate for real-world implementation. Both the Alex-Net and the SVM/LSTM model share the incorporation of a mix of cameras and LiDAR sensors despite their notable methodological variances. The findings show that the SVM and LSTM models perform better, which may be related to the much bigger dataset of 180,000 frames that were utilized in their creation.

A different method of image processing in the context of autonomous cars is presented in the study by [101], demonstrating the use of a fisheye camera. With its wide 360-degree field of vision, this kind of camera eliminates the need for several cameras in a single system. However, one significant issue with this technique is the distortion caused by fisheye lenses. To overcome this difficulty, the research decided against using the Local Binary Pattern. This method compromises picture quality by giving each pixel a binary value (0 or 1) depending on its brightness level. Instead, the suggested model used zoom augmentation to correct for distortion, which included changing the camera's focal length inside the dataset. A Gaussian distribution was used to aid in categorization further. The model used the ERFNet standard convolutional neural network (CNN). Using the Intersection over Union (IoU) value—a scale from 0 to 1 that represents the difference between ground truth and projected values—the findings presented in the research showed acceptable performance. This metric, which replaces mean average precision (mAP), [39], was recorded as 0.568, signifying mediocre precision. Farag et al. conducted a comparable investigation [98], for autonomous driving, a method based on behavior cloning was used. The process included using recorded car behaviors to simulate driving situations and then using this dataset to train a convolutional neural network (CNN). During testing, the training data was obtained via a front-facing camera and included steering directives that were inspired by the driving behaviors of experienced drivers in urban and traffic situations. The vehicle's motions were carefully captured, measured, and used as the basis for the training dataset.

A version of the Gradient Descent optimization approach was used for model training, repeatedly changing the network's parameters to maximize performance. Several image augmentation methods were used for the input photographs, such as color normalization, cropping, flipping, and brightness and shadow modifications. The training data was improved in terms of variety and quality by integrating supplemental datasets, such as Simulator Generated Data and Udacity Supplied Data [40]. Albeit since the car repeatedly veered off the road during testing, demonstrating subpar performance, the model produced very worthless results. The neural network's learning and enhancement capabilities were limited over time due to its notable lack of vast memory. This restriction probably made the model function less well than it should have, highlighting the need for more sophisticated and memory-enhanced designs in vehicle wheel technologies [102] [103]. Using an alternative method, [98] uses a 3D Convolutional Neural Network (3D CNN) to identify pedestrians near autonomous cars. The way their architecture is set up, pedestrian entities are identified in the object detection components and then processed by the CNN for pedestrian identification and classification (Fault Interpretation Using Neural Networks, n.d.) [104]. One notable use is the YOLO v3 Convolutional Neural Network architecture, which is similar to other approaches in the field. The neural network's input layer is the 3D point cloud obtained from LiDAR sensors. Variables such as fuzzy enhancement and color-based enhancement are crucial for data augmentation throughout the training program. The model means Average Precision (mAP) increases significantly under this augmentation regime, with a maximum margin of 0.85% between them. Performance analysis using datasets from Waymo and KITTI shows an accuracy measure between 95% and 99% on various datasets. This indicates good results with potential for enhancement since the datasets used had low variation [67], [99]. By introducing a technique based on depth and ego-motion optimization, the scientists hope to make careful picture processing easier for autonomous cars. The movement of a camera is a necessary component of ego-motion as it records the environment of moving vehicles.

According to the authors, [100] depth estimation is a difficult geometric problem that is often solved using linear mathematical paradigms. Through a posture estimate network, their technology simultaneously integrates RGB pictures and related feature maps. Predictions of object edge depth are strengthened using a contour loss function to improve accuracy. The PoseNet neural network, which repeatedly combines RGB pictures and feature maps after processing, enables the iterative improvement of accuracy across time epochs. One noteworthy feature of the network design is the activation of the Rectified Linear Unit (ReLU). Though the model can overcome noise-related difficulties, its significant computational complexity and resulting loss function make it difficult to use in practical operational settings [14]. Research [18] use the coordinate attention block-enhanced ResNeSt Convolutional Neural Network model to support the region of interest detection paradigm in the model. In addition to lowering computing load across several cycles, the coordinate attention block design enables the AI to choose to attend to important characteristics inside data or images a key feature for autonomous cars.

5. Conclusion

With a focus on generative models to mimic 3D vehicle wheels, the research applies deep learning approaches to computer-aided design (CAD) and computer-aided engineering (CAE) systems in this ground-breaking work. At the forefront of cutting-edge developments in design and engineering, the study investigates substitutes such as generative adversarial networks (GANs), variational autoencoders (VAEs), and convolutional neural networks (CNNs) to address problems with traditional CAD/CAE processes. Aimed at revolutionizing design workflows and enhancing CAE simulations under real-world conditions, the research utilizes a diverse dataset to train deep learning models, anticipating more efficient generative design processes, improved simulation accuracy, and adaptable design solutions for diverse optimization objectives. The commitment to practical integration underscores its significance in reshaping the design and engineering landscape, promising efficiency, innovation, and precision. In the conclusive exploration, the research delves into the intersection of CAD, deep learning (DL), and generative design, specifically focusing on 3D vehicle wheel simulation in real-world conditions. It highlights the transformative potential of generative design, tracing its historical roots back to the 1970s and emphasizing its integration with DL techniques. Using Generative Adversarial Networks (GANs) within the context of 3D vehicle wheels, the study showcases the capability of generative models to create customized designs adhering to industry standards. The incorporation of topology optimization further enhances design exploration, demonstrating the iterative refinement of designs. The research extends its focus to the broader implications of generative design, particularly in creating lightweight, strong, and sustainable vehicles, aligning with the increasing prominence of electric vehicles.

Representing a comprehensive exploration of advancing CAE through DL, the study envisions a transformative shift in engineering and manufacturing applications. It emphasizes the role of ML and AI, particularly DL, in democratizing AI for design engineers and reducing simulation lifecycles. Noteworthy is the integration of CAE automation in simulating vehicle behavior and the introduction of diverse data-driven approaches for topology optimization. The proposed framework, powered by deep neural networks, CNNs, and GANs, aims to automate 3D CAD model generation and predict CAE results accurately, positioning the integration of DL into CAE as a paradigm shift in automotive engineering. This research thoroughly investigates the integration of deep learning within CAD/CAE systems, emphasizing generative models and 3D vehicle wheel simulation in real-world scenarios. The study explores various aspects of this integration, incorporating machine learning techniques such as K-means, Support Vector Machine, PCA, Gaussian process, neural networks, and reinforcement learning. It highlights the profound impact of deep learning on enhancing the design efficiency of 3D vehicle wheels, showcasing applications of convolutional neural networks, genetic algorithms, and reinforcement learning in optimizing wheel structures for strength, stiffness, weight, and aerodynamics. The research extends its focus to autonomous vehicles, discussing the crucial role of deep learning in image processing and sensor fusion techniques, representing a paradigm shift in automotive engineering. While acknowledging challenges such as computational costs and sensor limitations, the study underscores the transformative potential of deep learning in advancing CAD/CAE systems, promising more efficient, accurate, and innovative solutions for automotive design and simulation.

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