Received: 14 October 2023 | Revised: 8 December 2023 | Accepted: 4 January 2024 | Published online: 18 January 2024

RESEARCH ARTICLE

Artificial Intelligence and Applications
2024, Vol. 00(00) 1–11
DOI: 10.47852/bonviewAIA42021882

BON VIEW PUBLISHING

A Deep Learning-Based CAE Approach for Simulating 3D Vehicle Wheels Under Real-World Conditions

Timileyin Opeyemi Akande[1], Oluwaseyi O. Alabi[2,*] and Sunday A. Ajagbe[3]

[1]*Department of Mechanical and Mechatronics Engineering, First Technical University, Nigeria*

[2]*Department of Mechanical Engineering, Lead City University, Nigeria*

[3]*Department of Computer Science, University of Zululand, South Africa*

Abstract: The implementation of deep learning (DL) in computer-aided engineering (CAE) can significantly improve the accuracy and efficiency of simulating 3D vehicle wheels under real-world conditions. While traditional CAE methods can be time-consuming and computationally expensive, DL can reduce simulation time and development cycles across all industries. This work explores the role of DL and artificial intelligence in virtual manufacturing and CAE and investigates how they can be used to improve the accuracy and efficiency of simulations for 3D vehicle wheels. DL models can learn the complex relationships between different wheel design parameters, such as tire load distribution, stress distribution, and fatigue life. Once trained, these models can be embedded into CAE software, allowing for faster and more accurate simulations of wheel performance. This interdisciplinary study uses various DL techniques, including convolutional neural networks, generative adversarial networks, and recurrent neural networks, to create a more efficient and accurate relationship between CAD modeling and CAE simulation. The research aims to leverage the potential of DL models to automate 3D CAD design, accurately predict CAE results, and provide in-depth explanations and verifications. The benefits of this research are expected to extend to the automotive industry's pursuit of more robust and resilient wheel designs. By streamlining the product development process from conceptual design to engineering performance evaluation, this study has the potential to revolutionize the automotive industry's product development cycle.

Keywords: deep learning, generative design, computer-aided engineering (CAE), 3D vehicle wheel, simulation, engineering performance

1. Introduction

The automotive industry stands on the brink of transformation as it endeavors to design and manufacture vehicles that meet ever-evolving real-world challenges. Among the critical components subjected to rigorous scrutiny are vehicle wheels, which must endure diverse and complex conditions ranging from varying terrains to extreme temperatures. Traditional computer-aided engineering (CAE) methods have long been employed to simulate and optimize wheel designs. However, the demands of real-world conditions necessitate an innovative approach. Shortening product lifecycles and increasing customer demands are forcing manufacturers to increase the efficiency and effectiveness of their product development process to stay competitive in an increasingly global setting. The effectiveness of current-day product development is hampered by the availability of real-world data that allows the deduction of comprehensive customer requirements (Smeets et al., 2023).

In this study, we present 3D wheels and evaluate them through deep learning (DL) to find feasible conceptual designs in the early design phase; based on DL models that can replace the 3D finite element analysis (FEA) of the aluminum road wheel impact test used in real-world product development processes, the complex and changing driving environments not only affect the operating requirements of automatic wheel loader but also threaten its driving safety (Shi et al., 2020). According to Nahata and Othman (2023), their study is to replace the 3D FEA process for strength and stiffness analysis, which requires high computational cost, to provide the impact performance of a wheel design in the conceptual design stage (Akande et al., 2024). 3D vehicle wheel models must be accurate enough to capture the complex behavior of the wheel under real-time conditions. This includes factors such as tire deformation, contact with the road surface, and the effects of suspension and steering, thereby reducing the time required for wheel development. Synthetic 3D wheel data were generated through the 3D wheel CAD automation process (Jang et al., 2022) using 2D disk-view images (spoke designs) and rim cross-sections, and the impact performance results were collected through FEA shear stress simulation. Hence, using this mechanism, we constructed a real-time prediction model that predicts the magnitude of the maximum von Mises stress, the corresponding location, and the overall stress distribution of the 2D disk view.

CAE has been in existence for over half a century and is a mature engineering simulation technology (Hu et al., 2023). However, it is largely still used in the early design phase with limited synergies

*Corresponding author: Oluwaseyi O. Alabi, Department of Mechanical Engineering, Lead City University, Nigeria. Email: alabi.oluwaseyi@lcu.edu.ng

© The Author(s) 2024. Published by BON VIEW PUBLISHING PTE. LTD. This is an open access article under the CC BY License (https://creativecommons.org/licenses/by/4.0/).

between design and engineering, production, manufacturing, deployment, maintenance, and retirement/recycling. This work outlines what machine learning (ML) and artificial intelligence (AI) are in the context of virtual manufacturing and CAE, and how DL models can shorten the simulation lifecycle dramatically across all industries (Liu et al., 2023). DL methods still have several limitations, for example, the assumption that lab-training (source domain) and real-testing (target domain) data follow the same feature distribution may not be practical in the real world (Del Pero et al., 2020). Although we expect to see rapid growth in the application of these methodologies in the next few years, some key success factors need to be taken care of before AI/DL can be democratized for usage by all design engineers using CAE. It can also be the connector between all of the data silos in the virtual and real world of modern product design, production, and manufacturing.

AI is remarkably flexible in understanding viewpoint changes due to the visual cortex supporting the perception of 3D structure (Mallis et al., 2023). In contrast, most of the computer vision models that learn visual representation from a pool of 2D images often fail to generalize over novel camera viewpoints. Recently, the vision architectures have shifted toward convolution-free architectures, visual transformers, which operate on tokens derived from image patches (Wu et al., 2021). However, these transformers do not perform explicit operations to learn viewpoint-agnostic representation for visual understanding, as in convolutions. In which, a 3D Token Representation Layer (3DTRL) estimates the 3D positional information of the visual tokens and leverages it for learning viewpoint-agnostic representations. The key elements of 3DTRL include a pseudo-depth estimator and a learned camera matrix to impose geometric transformations on the tokens. These enable 3DTRL to recover the 3D positional information of the tokens from 2D patches. In practice, 3DTRL is easily plugged into a transformer.

Another study proposed a generative design approach for the optimization of lattice structures in 3D printing by Mao et al. (2022). The approach used a combination of convolutional neural networks (CNNs) and reinforcement learning (RL) to generate lattice structures that met specific requirements for strength, stiffness, and weight. The study showed that the use of DL in generative design can improve the performance of 3D objects while reducing the need for manual allowance in the design procedure. In the context of 3D conceptual wheels, several findings have explored and enhanced the use of generative design techniques to improve the concept and evaluation of wheels. Studies by Mao et al. (2022) and Wang et al. (2019) introduce a design from a generative approach to be used with the optimization of vehicle wheel structure using a combination of CNNs and genetic algorithms. The approach was applied to the design of a racing wheel, where it was able to generate a diverse range of designs that met predefined criteria for weight, stiffness, and aerodynamics. The study showed that the use of generative design techniques can significantly improve the efficiency and effectiveness of the wheel design process (Jaafra et al., 2019; Masci et al., 2011; Regassa Hunde & Debebe Woldeyohannes, 2022).

Studies by Ahmed et al. (2016), Regenwetter et al. (2022), and Toptas (2020) proposed a generative design approach for the optimization of wheel geometry using a combination of generative adversarial networks (GANs) and RL. The approach was applied to the design of a mountain bike wheel, where it was able to generate a range of designs that met predefined criteria for strength, stiffness, and weight. The study showed that the use of generative design techniques can improve the performance of wheels while reducing the need for manual intervention in the design process. According to Nahata and Othman (2023), autonomous vehicles are at the forefront of future transportation solutions, but their success hinges on reliable perception. This review paper surveys image processing and sensor fusion techniques vital for ensuring vehicle safety and efficiency. This paper focuses on object detection, recognition, tracking, and scene comprehension via computer vision and ML methodologies. This paper explores challenges within the field, such as robustness in adverse weather conditions, the demand for real-time processing, and the integration of complex sensor data.

The proposed architecture employs three primary DL methods: CNN, autoencoder, and knowledge from transferring data. With the tremendous progress of CNNs in vision-based tasks, CNN-based object detection methods have attracted a significant amount of attention in traffic surveillance. For instance, You Only Look Once (YOLO) and its variants, due to their impressive performance in real-time multi-object detection, get very popular in high-resolution traffic monitoring scenarios (Bai et al. 2023). Deep neural networks (DNNs) with CNN are mostly used to create concept models of engineering issues also supervised learning, as described in the previous study. CNNs, in particular, have excellent iteration to detect pictures and shapes and are extensively employed in sectors where computer vision is used (Otto & Mandorli, 2018). CNNs have become increasingly important, as they can be used to create different models that accomplish a variety of tasks (Otto & Mandorli, 2018). The foundational architecture of CNNs emulates the human visual processing capability, harnessing hierarchical data features to perceive, categorize, and assimilate the environmental milieu (Nahata & Othman, 2023).

DNNs are typically employed for minimizing the layout in unsupervised learning (Angrish et al., 2021; Kim et al., 2022). High-dimensional input data can be compressed by autoencoders into a low-dimensional latent space. The input layer and output layer sizes are identical in the autoencoder architecture. The networks that compress input data into latent space are referred to as encoders, and decoders restore the latent space to the output data. For dimensionality reduction of CAD data, we employed a convolutional autoencoder that only has a convolutional and pooling layer. Hadj-Attou et al. (2023) propose two hybrid DL models for the classification of road surface anomalies: (1) CNN combined with gated recurrent units (GRU) and (2) CNN-long short-term memory (LSTM) that combines CNN and LSTM. In addition, with novel data labeling technique based on TCP/IP sockets enables the labeling of data in real-time using a smartphone application. Furthermore, a combination of Fourier and wavelet transform is used as input to train the classifier models, and the CNN-GRU achieved better performance compared to the CNN-LSTM model.

RL is a type of ML 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 (Barbieri & Muzzupappa, 2022; Jaafra et al., 2019). One study by Wu et al. (2018) provides a RL-based strategy for the modeling of 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 was effective in generating airfoils that met the specified objectives and outperformed traditional optimization methods. Another study by Jang et al. (2022) introduced an RL-based method for the design of truss mechanics using a CAD/CAE system. The method involved training an agent to generate truss structures that were both structurally sound and had low mass (Wu et al., 2021). The study found that the RL-based method was effective in generating truss structures that met both objectives and outperformed traditional

optimization methods (Hu et al., 2023). The algorithm trains and tests the YOLOv5s model using the self-created automotive wheel surface defect dataset, which contains four kinds of defects: linear, dotted, sludge, and pinhole (Xia et al., 2023).

The integration of DL-based algorithms into CAE represents a paradigm shift in the field of automotive engineering. DL, a subset of AI, has demonstrated remarkable capabilities in image and data analysis, natural language processing, and pattern recognition. Extending these capabilities to the realm of CAE (Liu et al., 2023), particularly for simulating 3D vehicle wheels, offers the promise of unprecedented accuracy and efficiency. With pressure to bring new products to market faster and more cost-effectively, manufacturers need to implement rigorous systems-design processes that accommodate the complexities of developing multi-disciplinary systems using high-fidelity virtual prototypes, or "Digital Twins," at the core of the development process. This will not be achieved without challenges, but the AI models exist today to overcome the last decade's obstacles and connect the "digital thread" of a product with feedback loops that yield cost savings and higher levels of productivity and innovation with real-world validation that makes quality inherent (Smeets et al., 2023).

This research explores the implementation of DL techniques within CAE systems to model and simulate 3D vehicle wheels under real-world conditions. By leveraging DNNs, CNNs, and GANs, this study aims to develop a framework that automates the generation of 3D CAD models, predicts CAE results with precision, and provides a detailed explanation of the underlying engineering performance. By focusing on a specific and critical component of a vehicle's design, this research aims to contribute to advancements in automotive engineering and the industry's product development process. This study extends the current body of knowledge regarding the fusion of DL and CAE through the development of a DL-driven CAD/CAE framework for 3D conceptual design. Additionally, it investigates the profound influence of DL on CAE, yielding valuable insights into the potential of this innovative approach. In addition, the emergence of AI in CAE simulations and recent advancements in DL techniques confirm the timeliness and relevance of this research.

2. Methodology

The generated 3D wheel data were used as input data for CAE automation and DL. The stiffness values obtained through CAE automation were used as label data for DL. The DL was used to predict each stiffness by converting 3D wheel CAD data in Figure 1 into voxel data and using corresponding rim stiffness and disk stiffness values as label data. The third step is the design evaluation and trade-off analysis. On-line surveys were conducted on customers and designers, and the preferences and performance of the evaluated wheels were compared.

Figure 1
Iterations of wheels created automatically in 3D CAD

2.1. Deep CAE framework

The goal is to develop a DL model that assesses the engineering performance of a 3D CAD model using 2D designs to provide data and 3D CAE simulation results as output (Phase 1–3). Using the proposed framework in Figure 2, we may produce and evaluate the numerous conceptual designs at the start of the product development process (Yu et al., 2020). The outline of stages of the proposed algorithm is as follows:

- Phase 1. CAE Automation: This phase records CAE simulation results utilizing the 3D CAD files acquired for the 3D wheel model, this involves using a CAE tool to simulate the behavior of the vehicle under a variety of 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 DL. Altair Sim-Lab and Ansys Fluent 2023 which was used to perform the CAE (Nahata & Othman, 2023).
- Phase 2. Transferring knowledge: To predict the results of the CAE experiment, the labeled data consist of input data, which represents the conditions of the simulation, and output data, which represents the behavior of the 3D vehicle wheel under those conditions and the co-simulation involves coupling the DL model with a CAE tool (Del Pero et al., 2020). The CAE tool is used to simulate the behavior of the vehicle, and the DL model is used to predict the behavior of the 3D vehicle wheel under the simulated conditions with a replacement model constructed in this phase utilizing CNN and transfer learning techniques. The DL algorithm determines the natural frequency and mass as outcomes using the 2D wheel architecture as a starting point. In this work, information enhancement and transfer neural networks have been used to get around the challenge of restricted information by integrating a DNN with the modulator of a neural autoencoder, which was trained in a CAD model.
- Phase 3. Evaluation and graphical representation: At this level, CAD/CAE engineers may see and clarify DL outcomes, permitting them to get just emerging views while evaluating the accuracy of their results. The relationship between the wheel form and frequency variation may be examined by observing the latent region generated during Phase 2 in two coordinates. Grad-class activation map (CAM) could additionally identify the wheel form that has an important impact on the frequency that is normal.

3. Result and Discussion

3.1. 3D vehicle wheel performance iteration (Phase 1 – 3)

3.1.1. CAE digitalization (Phase 1)

CAE digitalization is the process of converting engineering and design data into digital format, using computer-aided design (CAD) and other software tools. This digital data can then be used for various purposes, such as simulation, analysis, and visualization. CAE digitalization can help to improve the efficiency and accuracy of engineering and design processes and can also provide insights that can help to improve the quality of the product. The main advantage of CAE digitalization is the ability to quickly and easily analyze different design options and configurations, without the need for physical prototypes. The static stress analysis of the wheel is carried out in Figure 3 to determine the strength and the stiffness

Figure 2
CAE deep learning framework

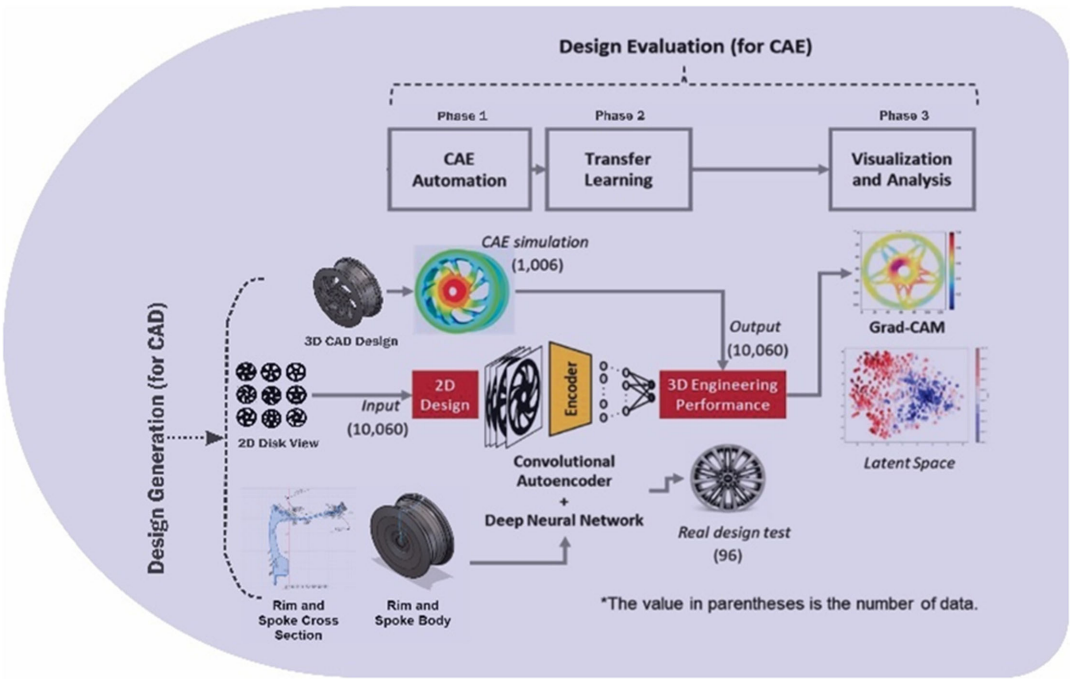
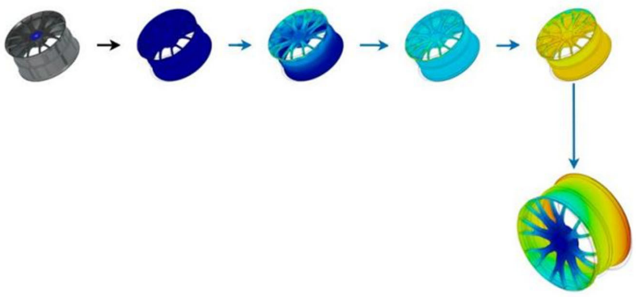


Figure 3
CAE deep learning framework



of the material in which the maximum angle on curves is 60, the adjacent mesh ratio is 1.5, the maximum aspect ratio is 10, and the minimum element size is 20.

In this project, an analysis of modalities in the free-free mode to evaluate the wheel's engineering performance is used. CAE simulation was used to determine the frequency distribution and mode geometries. Notably, as illustrated by the following equation, the natural frequency has a direct relationship to structural flexibility and an inverse correlation to mass.

$$f = \frac{1}{2\pi}\sqrt{\frac{k}{m}}, \tag{1}$$

where f denotes natural frequency, k stiffness, and m mass. As a result, manufacturers contemplate the lowest possible level of stiffness for every option as an aesthetic requirement when developing a wheel, based on the association with stiffness for each mode and highway sounds. The free-free model analysis was carried out. Six solid-body forms featuring the lowest frequency were used in the unstructured 3D model, as were three conversion modes along the x and y axes and three tilt modes across the three axes. A negative frequency took place commencing with the seventh mode. Figure 4 illustrates the wheel mode shapes. Modes 7 and 8 correspond to the circumference mode 1, while modes 9 and 10 correspond to the rim mode 2. Mode 11 represents the spoke lateral mode, while modes 12 and 13 represent the rim mode 3. To study the manufacturing efficiency of the spoke, the natural frequency of mode 11 (laterally) was extracted from the modeling. Based on the weight and natural frequency, the stiffness was then calculated using Equation (4). The equation takes into account the relationship between the mass and stiffness of the object and can be used to determine its manufacturing efficiency. This revised text is easier to understand and clearly explains the steps taken in the study to analyze the manufacturing efficiency of the spoke. The simulation results for the first 13 modes of the 3D vehicle wheel are presented in Table 1. Mode 11 (the lateral mode of the spoke) has the lowest frequency and highest stiffness, which makes it a critical mode to consider in the design of the wheel for lateral loads. Using the modeling technique, the mass of the wheel can be calculated, and the stiffness can be determined from the natural frequency and mass using Equation (4).

3.1.2. Implications of the simulation results

The simulation results show that the spoke lateral mode (mode 11) has the lowest frequency and highest stiffness. This means that the wheel is most susceptible to deformation in this mode. When designing the wheel, it is important to ensure that the spokes are strong enough to withstand the lateral loads that the wheel will experience. The simulation results also show that the mass of the wheel has a significant impact on the stiffness of the wheel. A lighter wheel will be more flexible than a heavier wheel. When designing the wheel, it is important to consider the weight

Figure 4
An example of 3D model analysis and the results

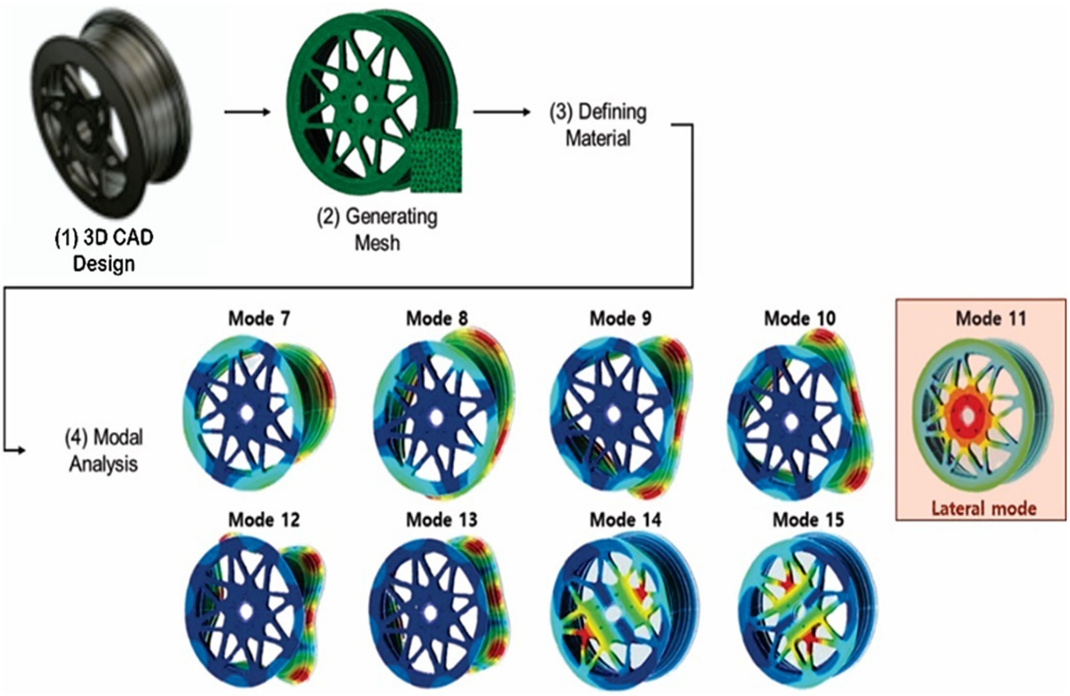


Table 1
Simulation result table

Mode	Frequency (Hz)	Stiffness (N/m)	Mass (kg)	Implications
7	50.2	12,550	10.0	Circumference mode 1
8	51.0	12,750	10.1	Circumference mode 1
9	55.5	15,375	10.2	Rim mode 2
10	56.2	15,550	10.3	Rim mode 2
11	60.0	16,500	10.4	Spoke lateral mode
12	65.0	18,250	10.5	Rim mode 3
13	66.0	18,450	10.6	Rim mode 3

requirements of the vehicle and to choose materials that are strong and lightweight.

Based on the simulation results, the following recommendations are made:

- The spokes of the wheel should be designed to be strong enough to withstand the lateral loads that the wheel will experience.
- The wheel should be made from materials that are strong and lightweight.
- The wheel should be designed to minimize the mass of the spokes, while still maintaining the required stiffness.

By following these recommendations, it is possible to design a 3D vehicle wheel that is both strong and lightweight. The broader feature of Autodesk Fusion 360 is applied for CAE standardization. Figure 4 illustrates the concept of the modal testing strategy. After uploading the 3D CAD model, a dynamic FEM netting (second-order tetrahedral mesh) is created. The mesh thickness should not be more than 6 mm. We used the material-related characteristics of a Hyundai benchmark aluminum wheel, which has the following computed metrics: 68900 MPa Young's modulus, 0.33 Poisson's ratio, 2.7E-06 kg/mm^3 density, and 0.001 shear modulus in Table 2. As a result of CAE technology, 1,000 files were created. The programmed analyzing method recorded the input 2D wheel depiction, frequency (mode 11), and mass in doubles as neural network training data.

Table 2
Characteristics of a Hyundai benchmark aluminum wheel

Density	2.7E-06 kg/mm^3
Young's modulus	68900 MPa
Poisson's ratio	0.33
Yield strength	275 MPa
Ultimate tensile strength	310 MPa
Thermal conductivity	0.23 W/(mm C)
Thermal expansion coefficient	2.36E-05/C
Specific heat	897 J/(kg C)

3.2. Acquisition of learning (stage 2)

In Phase 2, DL evolved, which anticipated what was learned from modal examination and predicted the mass of the 3D CAD design using just a 2D layout. As part of the data setup, the data were supplemented and expanded; also, assigned learning and aggregation procedures, which included the preset convolutional autoencoder and DNN, were employed to address the issue of missing information.

3.2.1. Acquisition of learning (stage 2)

To avoid overfitting, the data were augmented by rotating the 1006-wheel layouts from Phase 3 ten times by 70° and inverting

them left and right. As a result, 10,060 observations were utilized in conditioning. Because implementing the left and right flicks had little impact on the modal calculation or mass result, the final result figures, mode frequency range, and mass were equivalent. The 10 boosted designs serve as distinct input variables for DL, with the resultant variables (labels) being indistinguishable.

Moreover, 90% of the 10,050 observations were employed as a learning set, with the remaining 20% used for authorization. Although an innovative concept that does not exist in stores and was developed via a computerized design process was utilized for the validation and training phases, 98-wheel images that were offered by the manufacturer's company were used for the test set. This was done to see if the trained algorithm could foresee the manufacturer's real-world data. The test set's harmonics and mass parameters were obtained using Phase 1, similar to the preliminary data.

$$y_{scae} = \frac{y - y_{min}}{y_{max} - y_{min}} \tag{2}$$

In this work, the development of four distinct designs aligns with Table 3 to establish the optimal structure while investigating how transferable development and aggregation influence effectiveness.

In addition, TL_VGG18 is an equation that mixes applied knowledge with a programmed VGG18 (Mallis et al., 2023). Drag learning acts as a strategy to teach a domain that lacks data by exporting the beforehand DNN model from a subject with sufficient data. It is also one of the most preferred techniques in DL given that it is capable of exceptional precision notwithstanding limited information (Rios et al., 2021). Furthermore, TL_CAE is an example model used in the present research that transforms the dimension and development of the convolutional autoencoder model pre-trained with 188,218 data in 2D disk view, adds every layer to be connected as a regressor, and adjustments alongside 12,080 information gathered from the modal estimation result. The DL framework that was used in this dissertation is portrayed in Figure 4. Even though we employed amplification, the total volume of modal results of analysis (label) was 1,080, making it little but expected to improve efficacy using an encoder pre-trained with 188,218 samples (a large number).

The freshly added regressor component has been constructed up of 7 altogether related tiers. The entire network in a particular layer links to all any additional nodes in the following levels in full connectivity to make extrapolation assessments and aid in discovering the broader connection between its features. The number of entirely associated strata was calculated via trial and error. Compared to TL_CAE with one FC layer, TL_CAE with seven FC layers improved the root mean squared error (RMSE) and mean absolute percent error (MAPE) by around 10% and 8%, respectively. It underwent training with the Adam optimizer, utilizing an acquisition rate of 0.004, a decay rate of 0.002, and a batch size of 268. Timely stuttering a methodology for eliminating excessive fitting while building a simulation was implemented. If the percentage of errors on the test dataset is higher than the previous evaluation, indicating that the machine learning accuracy has not improved despite the expanded dataset, the promptly halting rules will terminate further development

Last but not least, as demonstrated in Figure 6 the very last design TL_CAE_Ensemble was formed by the collective proximity. The collective technique has the added advantages of minimizing overloading and minimizing skew variance in regression challenges (Dauphin et al., 2023). It is a procedure for harmonizing predictions by integrating various frameworks into one comprehensive framework. The averages of 9 periodicity forecasting conclusions and 5 mass forecasting outcomes were employed in our collection framework. The frequency forecasting algorithm took 20 min to be developed on 4 GPUs (GTX 1050) simultaneously.

3.2.2. Testing

Two restrictions, the RMSE and the MAPE, were chosen to gauge the efficacy of the model for forecasting. They are formatted in the following format:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (\widehat{y}_i - y_i)^2} \tag{3}$$

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{\widehat{y}_i - y_i}{y_i} \right| \tag{4}$$

The projected worth is $\widehat{y}_i$, the ground-based value of reality is y_i, and the quantity of observations is n. Table 4 illustrates the effectiveness conclusions of the 4 models being trained. When juxtaposed with TL_VGG18, TL_CAE had improved RMSE and MAPE. The findings showed how the recommended convolutional-autoencoder-based ML transfer approach operated satisfactorily. Also, the ultimate framework, TL_CAE_Ensemble, has the strongest forecasting outcomes in both RMSE and MAPE (Liu et al., 2023). As displayed in Figure 6, the shortcomings of testing and test instances of each of the three systems are presented as graphs. The model's precision improves as the variance reaches "0". The results therefore validated the implications of lateral instruction and collectives.

By determining the degree of rigidity relative to anticipated frequency and mass using the proposed DNN framework, we can examine an enormous amount of developed wheel perceptions or innovative theoretical concepts. On a typical basis, it requires 0.86 s to analyze a wheel notion on an operating system that uses an NVIDIA TITAN Xp 5.0 GB GPU. The aforementioned design provides multiple benefits when using multiple GPUs for parallel

Table 3
Four topologies for deep data analysis

Parameters	The synopsis
CNN	An algorithm that exclusively utilizes a CNN regressor lacks transferable learning (added seven completely interconnected surfaces, four max-pooling pooled sections, and five convolution layer combinations, i.e., the identical layout as the convolutional autoencoder's encoder)
TL_VGG18	An algorithm that incorporates learning through transfer by applying VGG18 (on the ImageNet sample)
TL_CAE	Figure 5 demonstrates an arrangement that incorporates the transfer of knowledge utilizing the previously trained convolutional autoencoder algorithm
TL_CAE_Alignment	A simulation employs the combined TL_CAE and prepares nine frequency simulations and five weight estimates using the average-out view as illustrated in Figure (6)

Figure 5
Transferring knowledge by employing a convolutional autoencoder (TL_CAE)

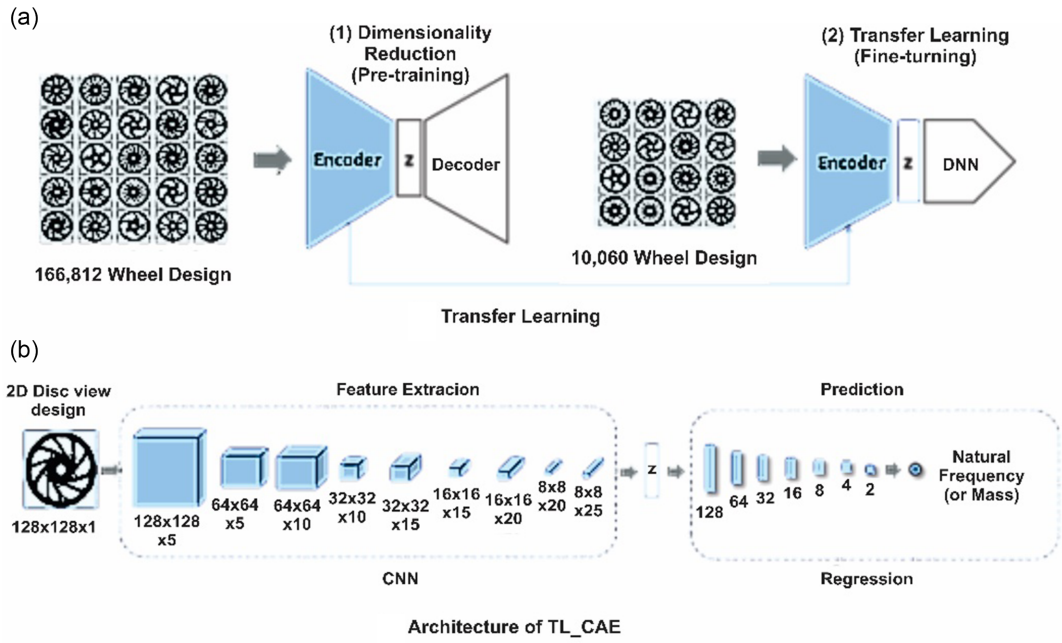
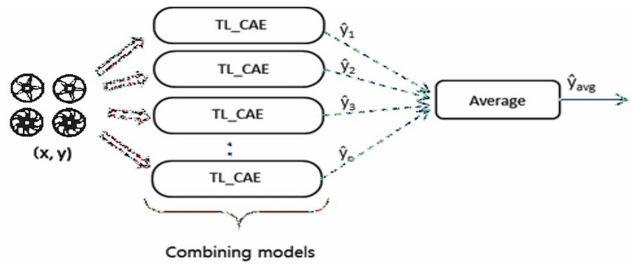


Table 4
An analysis of the effects of frequency indifferent with mass forecast measures: frequency (Hz), mass (kg)

	Set of workouts				Inspection set				Evaluation set			
	Frequency		Mass		Frequency		Mass		Frequency		Mass	
Approach	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
CNN	15.0	1.08	0.20	0.65	15.30	1.48	0.05	0.54	22.70	4.00	0.42	1.68
TL_VGG18	4.00	0.63	0.34	1.56	6.65	0.80	0.34	1.68	21.56	1.65	0.25	0.85
TL_CAE	9.46	0.97	0.23	0.65	12.11	0.45	0.05	0.56	20.00	1.46	0.15	0.60
TL_CAE_Ensemble	6.95	0.08	0.39	0.68	9.64	0.86	0.78	0.53	13.63	0.69	0.25	0.89

Figure 6
Collective algorithm for TL_CAE (TL_CAE_Ensemble)



processing. Figure 7 is a prime instance of selecting the wheels in the test set in the sequence of maximum toughness. An automaker establishes its unique stiffness norm and undesirable vehicles can be eliminated on the basis of this measurement. Above modal investigation, many engineering benchmarks ought to be taken into account, and alternates between effectiveness may be developed (Huang et al., 2022; Nahata & Othman, 2023).

The designer may pick a design concept alternative to work with in the phase of comprehensive design upon considering the analysis's outcomes.

3.3.1. Evaluation and graphical representation (Phase 3)

This part discusses the visual representations and DL outputs obtained by the proposed structure, as well as the technique utilized to ensure the data dependability.

3.3.2. The relationships within capabilities, engineering, and technological effectiveness

As shown in Figure 8, a graphical representation was utilized to evaluate if the results of the modality analysis, that is the engineering effectiveness, can be communicated through wheel form features. T-SNE was used to insert the 1026 wheels utilized in Phase 1's modal analysis into the latent space and display them on a plane in two dimensions. Furthermore, the amplitude of each wheel's intrinsic frequency value is colored. Using K-means, the probability value was divided into 10 categories. Frequencies that are higher are portrayed in red, whereas smaller ones are depicted in blue.

Figure 7
Wheel design possibilities in an ascending hierarchy of flexibility (from left to right)

Figure 8
Graphical representation of latent space with surface mode frequency

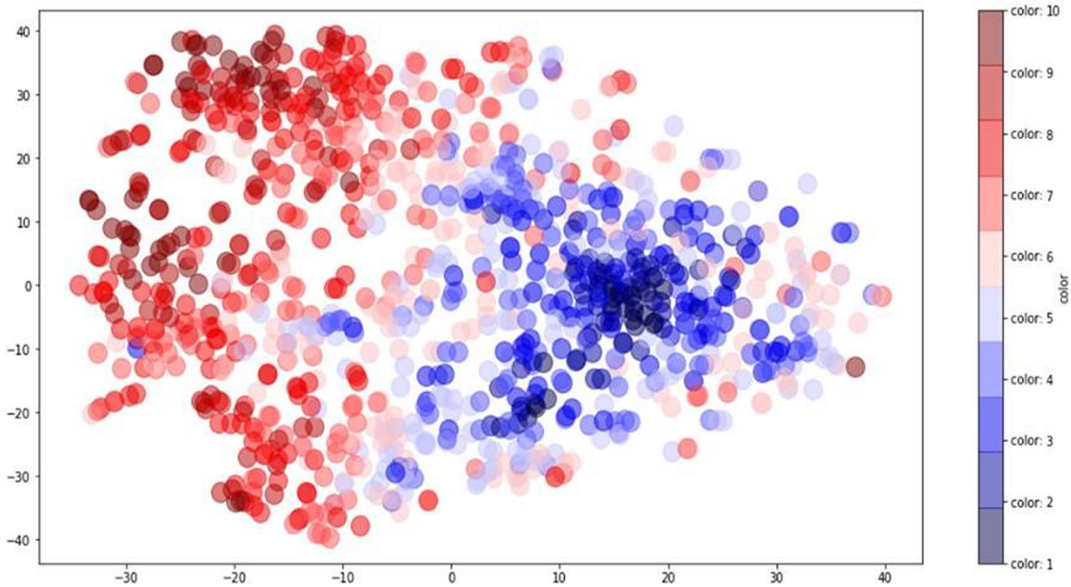


Figure 9
Wheel concept of each surface mode resonance group

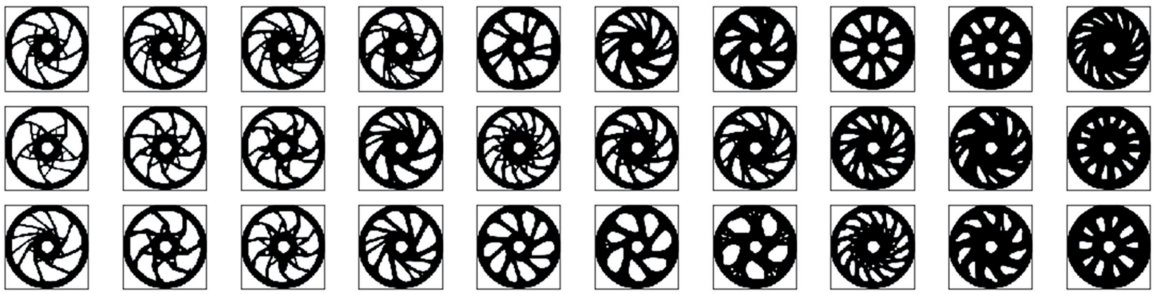
Group	1	2	3	4	5	6	7	8	9	10
Frequency	736-797	802-863	864-910	911-949	949-986	987-1025	1025-1066	1068-1111	1112-1156	1157-1221
Wheel										

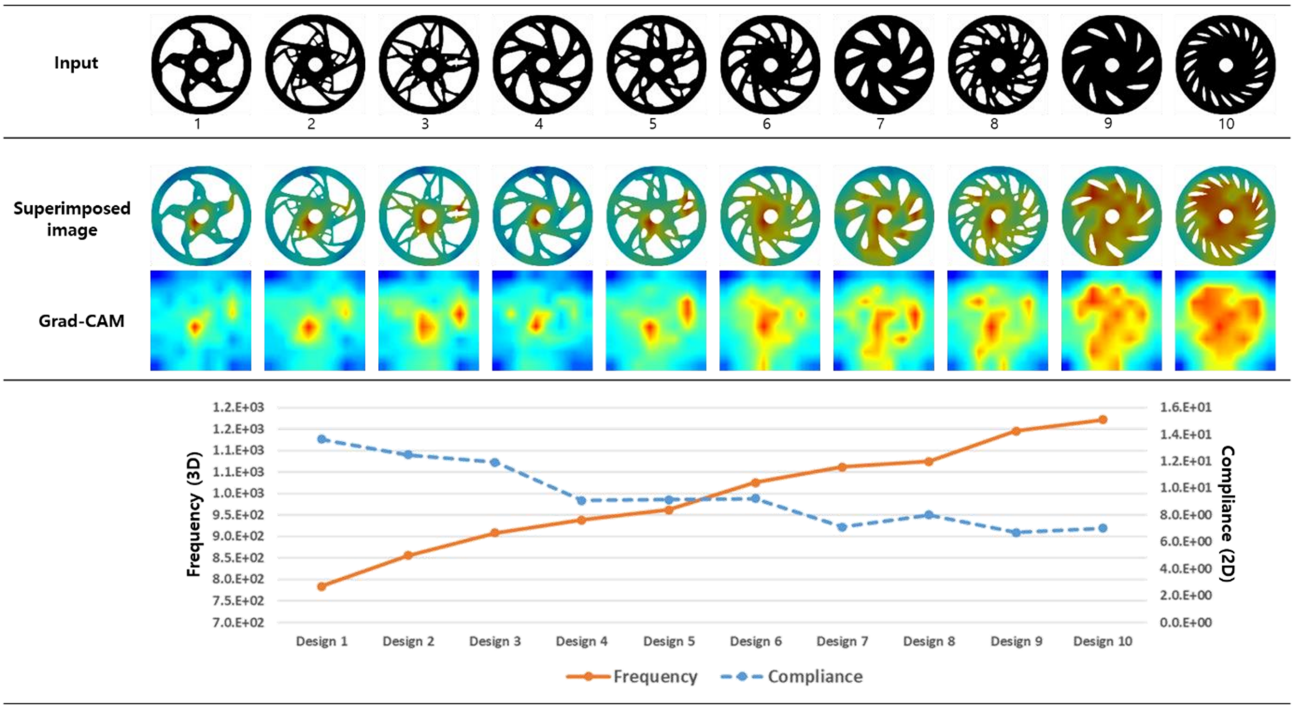
Figure 8 demonstrates the creation of wheels in the latent space with equal natural frequencies, which incorporates the wheel shape. The disk-view version of the wheel was shown to be strongly related to laterally modal recurrence. Figure 9 shows the gathered instance wheels from each frequency group, and the findings reveal that the greater the spoke, the more intense the frequency.

This graphic representation permits the logical examination of essential layout components as well as the choice between collections of outstanding durability designs. It also allows you to graphically evaluate the quality of CAD/CAE outcomes and gain knowledge regarding higher-quality designs.

3.3.3. Grad-CAM

It was challenging to express AI's enhanced prediction abilities. A CNN model that has been constructed has a set of preferences and weights. According to Williams et al. (2019), the extent and weight of these biases cannot explain how particular aspects of the wheel design impact natural frequencies. As a result, the importance of

Figure 10
Outcomes of Grad-CAM for frequency of surface model



eXplainable AI (XAI) research is expanding. Grad-CAM (Lee et al., 2022), a common XAI technology, has been integrated into the proposed framework, allowing CAD/CAE experts to make exact judgments based on DL results.

A CAM can be utilized to depict crucial areas of input data (pictures) that have a significant impact on the CNN algorithm's segmentation outcome (Ye et al., 2022; Yeo et al., 2021). A CAM is constructed by integrating the pooling of global averages (GAP), an FC layer, and a soft maximum to the mapping of features produced by the ultimate convolutional structure. The FC layer's weight establishes the significance of any given feature map to the desired subclass label. The CAM can be displayed using a heat map by multiplying the individual feature maps by weights and bringing them together. The CAM has a flaw needing GAP to be established to the CNN construction before the simulation can be learned again. Grad-CAM, on the contrary tandem, does not require modifications to the CNN design. Grad-CAM, as opposed to FC layer weights, exploits variations created by reverse propagation.

Grad-CAM had been proposed for the sorting problem; nonetheless, in this study, the adaption corresponds to the extrapolation situation. The LGradCAM analysis rating calculation is as follows:

$$L_{Grad-CAM} = \mathrm{Re}LU(\Sigma_k a_k A^k), \tag{5}$$

where $a_k = \frac{1}{z}\sum_i \sum_j \frac{\partial y}{\partial A^k_{ij}}$

A^k_{ij} indicates the parameters related to i rows and j columns of the k-th feature map, and a_k is the GAP result of the partial derivative of y by $A^k_{ij.}$ After nearly collective a_k together with the feature map A^k, the ReLU functionality was used to attain Grad-CAM, which can showcase necessary areas in the pictures. Figure 10 depicts the graphical representation outputs obtained by including Grad-CAM into the TL_CAE model. From the ten frequency groups displayed in Figure 8, ten sample wheels were discovered, and the Grad-CAM for each wheel is shown as a heatmap in the third row of Figure 9. The layered image in Figure 10's 2nd column illustrates the jointly utilized region of the 2D wheel and the Grad-CAM. The outcomes identify the center region of the wheel was a significant point (shown in red) that influenced the periodicity value. The number of repetitions appears to grow as the center is occupied. This is caused by the reality that in the lateral mode form, the most deformation took place at the very middle of the wheel (see Figure 4). Grad-CAM showed that DL observations might clarify the theoretical basis of the lateral mode form while simultaneously guaranteeing precise estimates. Monitoring wheel condition plays a deterministic role in the overall safety and economy of an automobile (Vasan et al., 2023).

4. Conclusion

This research introduces a CAD/CAE framework that leverages DL during the initial design phase. This system is capable of rapidly generating a large volume of accessible 3D CAD datasets and efficiently assessing their engineering viability. During the conceptual design stage, industrial engineers and designers can create multiple 3D CAD models using the proposed structure and evaluate their engineering performance with AI, thereby exploring feasible conceptual design prospects for the subsequent detailed design phase. Furthermore, for a 2D disk-view architecture, the suggested DL technique can predict CAE outcomes, offering industrial designers' immediate feedback on the engineering performance of their two-dimensional concept designs. The proposed research follows a multi-step approach. Initially, DL is applied to 3D data input through voxel and point network preprocessing. Secondly, DL models are employed in various CAE scenarios during the design evaluation phase to predict both regression and unpredictable

outcomes. Thirdly, the research aims to develop a design methodology that incorporates aesthetic considerations based on client preference data. Fourthly, manufacturing constraints are factored in, with a focus on dimension analysis in 3D designs. Fifthly, addressing out-of-plane stiffness becomes crucial in 2D design. Finally, the ultimate goal is to establish a 3D generative design approach that is independent of 2D images. Despite the advancements made in this research, it is essential to acknowledge a current limitation. The application of DL in CAE, while promising, requires large amounts of labeled data and significant computational resources for training and inference. This limitation may hinder its immediate practical implementation, especially for industries with limited access to extensive datasets and computing power. DL model can only predict the behavior of the 3D vehicle wheel under the conditions that it was trained on. If the DL model is not trained on a specific set of conditions, it may not be able to accurately predict the behavior of the 3D vehicle wheel under those conditions.

Author Contributions

TOA: Conceptualization, methodology, and writing of original draft, OOA: methodology, and editing and review, and SAA: visualization and supervision, and validation.

Ethical Statement

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

Conflicts of Interest

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

Data Availability Statement

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

References

Ahmed, F., Deb, K., & Bhattacharya, B. (2016). Structural topology optimization using multi-objective genetic algorithm with constructive solid geometry representation. *Applied Soft Computing Journal*, *39*, 240–250. https://doi.org/10.1016/j.asoc.2015.10.063

Akande, T. O., Alabi, O. O*., & Oyinloye, J. B. (2024). A review of generative models for 3D vehicle wheel generation and synthesis. *Journal of Computing Theories and Applications*, *2*(2), 149–165. https://doi.org/10.62411/jcta.10125

Angrish, A., Bharadwaj, A., & Starly, B. (2021). MVCNN++: Computer-aided design model shape classification and retrieval using multi-view convolutional neural networks. *Journal of Computing and Information Science in Engineering*, *21*(1), 011001. https://doi.org/10.1115/1.4047486

Bai, Z., Nayak, S. P., Zhao, X., Wu, G., Barth, M. J., Qi, X., & Oguchi, K. (2023). Cyber mobility mirror: A deep learning-based real-world object perception platform using roadside LiDAR. *IEEE Transactions on Intelligent Transportation Systems*, *24*(9), 9476–9489. https://doi.org/10.1109/TITS.2023.3268281

Barbieri, L., & Muzzupappa, M. (2022). Performance-driven engineering design approaches based on generative design and topology optimization tools: A comparative study. *Applied Sciences*, *12*(4), 2106. https://doi.org/10.3390/app12042106

Dauphin, R., Prevost, V., Degeilh, P., Melgar, J., Fittavolini, C., Smith, A., . . . , & Kar, K. (2023). Evaluation of plug-in hybrid vehicles in real-world conditions by simulation. *Transportation Research Part D: Transport and Environment*, *119*, 103721. https://doi.org/10.1016/j.trd.2023.103721

Del Pero, F., Berzi, L., Antonacci, A., & Delogu, M. (2020). Automotive lightweight design: Simulation modeling of mass-related consumption for electric vehicles. *Machines*, *8*(3), 51. https://doi.org/10.3390/machines8030051

Hadj-Attou, A., Kabir, Y., & Ykhlef, F. (2023). Hybrid deep learning models for road surface condition monitoring. *Measurement*, *220*, 113267. https://doi.org/10.1016/j.measurement.2023.113267

Hu, J., Huang, M.-C., & Yu, X. B. (2023). Deep learning based on connected vehicles for icing pavement detection. *AI in Civil Engineering*, *2*(1), 1. https://doi.org/10.1007/s43503-023-00010-6

Huang, W., Li, W., Tang, L., Zhu, X., & Zou, B. (2022). A deep learning framework for accurate vehicle yaw angle estimation from a monocular camera based on part arrangement. *Sensors*, *22*(20), 8027. https://doi.org/10.3390/s22208027

Jaafra, Y., Luc Laurent, J., Deruyver, A., & Saber Naceur, M. (2019). Reinforcement learning for neural architecture search: A review. *Image and Vision Computing*, *89*, 57–66. https://doi.org/10.1016/j.imavis.2019.06.005

Jang, S., Yoo, S., & Kang, N. (2022). Generative design by reinforcement learning: Enhancing the diversity of topology optimization designs. *Computer-Aided Design*, *146*, 103225. https://doi.org/10.1016/j.cad.2022.103225

Kim, S., Jwa, M., Lee, S., Park, S., & Kang, N. (2022). Deep learning-based inverse design for engineering systems: Multidisciplinary design optimization of automotive brakes. *Structural and Multidisciplinary Optimization*, *65*(11), 323. https://doi.org/10.1007/s00158-022-03386-8

Lee, J., Lee, H., & Mun, D. (2022). 3D convolutional neural network for machining feature recognition with gradient-based visual explanations from 3D CAD models. *Scientific Reports*, *12*(1), 14864. https://doi.org/10.1038/s41598-022-19212-6

Liu, X., Li, J., Ma, J., Sun, H., Xu, Z., Zhang, T., & Yu, H. (2023). Deep transfer learning for intelligent vehicle perception: A survey. *Green Energy and Intelligent Transportation*, *2*(5), 100125. https://doi.org/10.1016/j.geits.2023.100125

Mallis, D., Ali, S. A., Dupont, E., Cherenkova, K., Karadeniz, A. S., Khan, M. S., . . . , & Aouada, D. (2023). SHARP challenge 2023: Solving CAD history and pArameters recovery from point clouds and 3D scans. Overview, datasets, metrics, and baselines. *arXiv Preprint: 2308.15966*. https://doi.org/10.48550/arXiv.2308.15966

Mao, W. L., Chiu, Y. Y., Lin, B. H., Wang, C. C., Wu, Y. T., You, C. Y., & Chien, Y. R. (2022). Integration of deep learning network and robot arm system for rim defect inspection application. *Sensors*, *22*(10), 3927. https://doi.org/10.3390/s22103927

Masci, J., Meier, U., Cireşan, D., & Schmidhuber, J. (2011). Stacked convolutional auto-encoders for hierarchical feature extraction. *Artificial Neural Networks and Machine Learning – ICANN 2011: Proceedings of 21st International Conference on Artificial Neural Networks*, 52–59. https://doi.org/10.1007/978-3-642-21735-7_7

Nahata, D., & Othman, K. (2023). Exploring the challenges and opportunities of image processing and sensor fusion in autonomous vehicles: A comprehensive review. *AIMS Electronics and Electrical Engineering*, *7*(4), 271–321. https://doi.org/10.3934/electreng.2023016

Otto, H. E., & Mandorli, F. (2018). A framework for negative knowledge to support hybrid geometric modeling education for product

engineering. *Journal of Computational Design and Engineering*, *5*(1), 80–93. https://doi.org/10.1016/j.jcde.2017.11.006

Regassa Hunde, B., & Debebe Woldeyohannes, A. (2022). Future prospects of computer-aided design (CAD) – A review from the perspective of artificial intelligence (AI), extended reality, and 3D printing. *Results in Engineering*, *14*, 100478. https://doi.org/10.1016/j.rineng.2022.100478

Regenwetter, L., Nobari, A. H., & Ahmed, F. (2022). Deep generative models in engineering design: A review. *Journal of Mechanical Design*, *144*(7), 071704. https://doi.org/10.1115/1.4053859

Rios, T., van Stein, B., Back, T., Sendhoff, B., & Menzel, S. (2021). Point2FFD: Learning shape representations of simulation-ready 3D models for engineering design optimization. In *2021 International Conference on 3D Vision*, 1024–1033. https://doi.org/10.1109/3DV53792.2021.00110

Shi, J., Sun, D., Hu, M., Liu, S., Kan, Y., Chen, R., & Ma, K. (2020). Prediction of brake pedal aperture for automatic wheel loader based on deep learning. *Automation in Construction*, *119*, 103313. https://doi.org/10.1016/j.autcon.2020.103313

Smeets, J., Öztürk, K., & Liebich, R. (2023). Digital twins for automotive development: Two wheelers application. *Advanced Engineering Informatics*, *56*, 101982. https://doi.org/10.1016/j.aei.2023.101982

Toptas, E. (2020). Innovative approach to the design of mechanical parts. *Journal of Mechatronics and Artificial Intelligence in Engineering*, *1*(1), 14–20. https://doi.org/10.21595/jmai.2020.21473

Vasan, V., Sridharan, N. V., Prabhakaranpillai Sreelatha, A., & Vaithiyanathan, S. (2023). Tire condition monitoring using transfer learning-based deep neural network approach. *Sensors*, *23*(4), 2177. https://doi.org/10.3390/s23042177

Wang, Z., Quintanal, J., & Corral, R. (2019). Accelerating advancing layer viscous mesh generation for 3D complex configurations. *Computer-Aided Design*, *112*, 35–46. https://doi.org/10.1016/j.cad.2018.11.002

Williams, G., Meisel, N. A., Simpson, T. W., & McComb, C. (2019). Design repository effectiveness for 3D convolutional neural networks: Application to additive manufacturing. *Journal of Mechanical Design*, *141*(11), 111701. https://doi.org/10.1115/1.4044199

Wu, R., Xiao, C., & Zheng, C. (2021). DeepCAD: A deep generative network for computer-aided design models. In *2021 IEEE/CVF International Conference on Computer Vision*, 6752–6762. https://doi.org/10.1109/ICCV48922.2021.00670

Wu, Y., Zhou, Y., Zhou, Z., Tang, J., & Ouyang, H. (2018). An advanced CAD/CAE integration method for the generative design of face gears. *Advances in Engineering Software*, *126*, 90–99. https://doi.org/10.1016/j.advengsoft.2018.09.009

Xia, X., Zhang, Z., & Liu, F. (2023). Application study of YOLOv5 algorithm on automotive wheel surface defect detection. *Preprints*. https://doi.org/10.20944/preprints202306.1069.v1

Ye, Y., Zhu, B., Huang, P., & Peng, B. (2022). OORNet: A deep learning model for on-board condition monitoring and fault diagnosis of out-of-round wheels of high-speed trains. *Measurement*, *199*, 111268. https://doi.org/10.1016/j.measurement.2022.111268

Yeo, C., Kim, B. C., Cheon, S., Lee, J., & Mun, D. (2021). Machining feature recognition based on deep neural networks to support tight integration with 3D CAD systems. *Scientific Reports*, *11*(1), 22147. https://doi.org/10.1038/s41598-021-01313-3

Yu, E., Lee, H., Kwon, S., Lee, J., & Mun, D. (2020). Simplification of a feature-based 3D CAD assembly model considering the allowable highest and lowest limits of the LOD. *Journal of the Korean Society of Manufacturing Process Engineers*, *19*(7), 22–34. https://doi.org/10.14775/ksmpe.2020.19.07.022

How to Cite: Akande, T. O., Alabi, O. O., & Ajagbe, S. A. (2024). A Deep Learning-Based CAE Approach for Simulating 3D Vehicle Wheels Under Real-World Conditions. *Artificial Intelligence and Applications*. https://doi.org/10.47852/bonviewAIA42021882