Driving towards a greener future: The role of artificial intelligence and 3D printing in advancing energy-efficient vehicles

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Abstract. Based on the current complex climate environment, this paper reviews and analyzes the application of artificial intelligence (AI) and 3D printing technology in energy efficient vehicles. It first introduces the current background of global warming caused by increasing carbon emissions, in which the production of energy-efficient vehicles can mitigate this phenomenon, and then introduces the current cutting-edge AI technology and 3D printing technology. In related work, the author detailed the application of artificial intelligence in the field of autonomous driving and the application of 3D printing technology in the field of automotive manufacturing, such as self-powered tire strain sensors with safety data transmission and Selective Laser Melting (SLM) technology. In terms of research methods and applications, the author uses the You Only Look Once (YOLO) model in AI to simulate autonomous driving, and the speech dialog system (SDS) system to realize human-vehicle language interaction. Convolutional neural networks (CNN) are utilized to verify the compliance of automotive components. In the aspect of 3D printing, it introduces the advantages of SLM technology for printing aluminum as an automobile shell and Polylactic Acid (PLA) for automobile parts using Fused Deposition Modeling (FDM) technology. The following introduces the case experiments of detecting part defects with the CNN model and YOLO model respectively. Finally, based on the current technology, it looks forward to future technology trends and their impact on the automobile industry.

Keywords: Artificial intelligence, 3D printing,YOLO Object Detection,Convolutional neural networks

1 Introduction

The conclusions summarized by the United Nations organization are that the average global temperature of the planet is directly correlated with the density of greenhouse gases (GHG) in the air. Since the Industrial Revolution, there has been a steady increase in both the concentration and mean world temperatures. Carbon dioxide, the most prevalent GHG is mostly produced by burning fossil fuels[1]. Gasoline is the main fossil fuel for cars. The 2022 carbon dioxide emissions of the ground transportation sector, which is still increasing from + 8.8% to + 2.5% in comparison

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to 2021[2]. The automobile holds an indispensable role in people's daily transportation, yet the environmental pollution it generates remains a cause for concern. Therefore, developing new energy-efficient vehicles is one way to reduce GHG emissions. The author focuses on how to apply artificial intelligence and 3D printing in the development of energy-efficient vehicles.

By improving individual vehicle performance can reduce GHG emissions and mitigate the environmental impact of automobiles.

AI is a diverse and multifaceted technology, possessing the ability to amalgamate various domains such as cognitive processes, deep learning, emotional detection, man-machine interaction, information management, and choice process capabilities[3].

Artificial intelligence has undergone a developmental trajectory spanning over 70 years. Artificial intelligence was born at the Dartmouth Conference in 1956. During the 1980s, backpropagation neural networks gained widespread recognition, prompting rapid advancements in algorithm research based on artificial neural networks and significant improvements in computer hardware capabilities. In 2012, the advent of deep learning led to groundbreaking progress in artificial intelligence, particularly in speech and visual recognition algorithms[4].

The development of autonomous driving systems stems from the comprehensive integration of next-generation information technologies. This includes significant advancements in the automotive industry, breakthroughs in artificial intelligence, and the incorporation of the Internet of Things. These technologies collectively contribute to the evolution of self-driving vehicles, enabling more efficient, safe, and intelligent transportation solutions[5]. The future progression of autonomous driving hinges on the enhancement of real-time data processing capabilities and the assurance of seamless communication between vehicles and infrastructure. This will not only enhance road safety but also optimize traffic flow, culminating in a more efficient and sustainable transportation system.

At the same time, AI can also play a variety of roles in car production. AI can be used to design and optimize automotive production lines to automate production processes. For example, through the intelligent control of robots and automated equipment, efficient assembly and assembly processes can be achieved. AI can also be combined with Internet of Things (IoT) technology to enable intelligent manufacturing, enabling automotive production lines to be adaptive and self-learning, adjust production processes and parameters based on real-time data, and improve production efficiency and flexibility.

3D printing is an additive manufacturing technique used to create a wide range of complex shapes and assemblies from three-dimensional model data[6]. 3D printing is typically categorized into three main processes: Powder Bed Fusion, Photopolymerization, and Extrusion-Based Systems. 3D printing technology is increasingly playing a pivotal role in automotive production. Car manufacturers leverage 3D printing to create rapid prototypes, thereby accelerating the design and development process. This not only reduces costs but also enables design teams to test and refine car components more swiftly. Additionally, 3D printing allows for the creation of complex shapes and structures, resulting in lighter car parts that enhance fuel efficiency and overall performance.

2 Relative work

2.1 Application of Artificial Intelligence in vehicle development

With the development of Artificial Intelligence, many AI models have been applied in the automotive field, and a large number of researchers have conducted research based on the application of Artificial Intelligence.

The first application of artificial intelligence in cars is to train artificial intelligence to perceive, locate, and build maps. The second training AI decision-making capabilities, such as automatic parking, and path planning[7].

The key to autonomous vehicles (AVs) is to make the AI of a car understand its surroundings and make the right decision. In the area of autonomous vehicles, the application of AI technology is pivotal, encompassing various interdisciplinary subjects such as computational systems, data-driven algorithms, applied mechanics, and systems design. A quintessential example illustrating the integration of these technologies is exemplified by Hydra, a self-driving car invented by a university's automotive lab. Hydra is equipped with the NVIDIA Drive PX2 as its on-board Computing Unit (VCU), integrating a range of sensors, all of which are seamlessly connected to the VCU for sensing purposes[8]. Besides, they designed a computer system to process and analyze the information transmitted by these sensors and make corresponding decisions. Such AI-controlled autonomous vehicles have high accuracy for vehicle control and timely response to the surrounding environment, but the power of the onboard battery for such a powerful AI computing system will lead to a reduction in the mileage of the car, and its high manufacturing cost can not be ignored[8].

Regarding the application of AI in intelligent driver assistance systems, the following is a driving assistance system based on deep learning which effectively solves the task of traffic sign recognition. In the realm of intelligent driver assistance systems, an innovative approach utilizing deep learning has emerged to tackle the crucial task of traffic sign recognition. This system leverages a hybrid 2D-3D CNN model within the framework of transfer learning, demonstrating exceptional performance on real-world datasets. Transfer learning, a pivotal technique, facilitates enhanced learning within the target domain by leveraging pertinent knowledge from a source domain. The amalgamation of deep 2D CNNs with shallow 3D CNNs not only streamlines complexity but also expedites the training process. The primary model, Hybrid-TSR, is meticulously crafted to adeptly address the challenge of traffic sign recognition, essential for ensuring safe and efficient driving experiences. Meanwhile, the secondary modern, Hybrid-SRD, pioneers semantic detection of road space through a judicious blend of up-sampling and deconvolution operations, thereby further enhancing the system's functionality[9]. While the hybrid model reduces complexity compared to conventional approaches, it still requires sophisticated implementation and computational resources. The efficacy of transfer learning is contingent upon the availability and quality of relevant source domain data, posing challenges in domains with limited datasets.

2.2 3D printing in automotive technology innovation

3D printing technology has been widely used in the automotive manufacturing field because of its advantages of customized manufacturing, rapid prototyping, material saving, manufacturing complex structures, providing production flexibility, and reducing production costs. Here are some representative cases.

The first application example is a 3D-printed self-powered tire strain sensor with secure data transmission[10]. The research team first printed a strain sensor containing silver nanoparticles on the Caption film. Next, they developed a special ink for graphene that allowed it to perform REDOX reactions on the graphene. By controlling process parameters such as gas flow, velocity, and viscosity, they succeeded in creating a graphene oxide sensor with a uniform microstructure. After five processes, a graphene-based printed sensor with a thickness of 10 microns was finally obtained[10]. This sensor is mainly used to measure the strain generated by the tire during movement and convert it into a voltage waveform. The success of this technology fully demonstrates that 3d printing technology has broad prospects in automotive sensor printing.

SLM is a metal additive manufacturing process that employs powder bed fusion, extensively utilized in the production of highly customized and high-value components for industries such as biomedical, defense, aerospace, and automotive. Aluminum alloy is commonly used in SLM manufacturing because of its low weight, high durability, and superior resistance to corrosion[11]. The combination is also suitable for 3d printed car casings. At present, there are still some drawbacks to printing aluminum cars with SLM technology. For example, the cost of SLM printing aluminum is high, especially aluminum powder. The printed aluminum parts usually require complex post-treatment processes, such as heat treatment and surface treatment, to improve mechanical properties and surface quality. In addition, SLM is slow to print, especially for larger car casings, and the printing time can be quite long.

3 Methods

3.1 Artificial intelligence technology

Deep learning is a field of machine learning that automatically extracts features from large amounts of data by using deep neural networks. Through these features, deep learning systems can make predictions and decisions[12]. In the AI system of our car, we choose the YOLO model in deep learning to conduct real-time object detection, hoping to experiment with the autonomous driving function.

The YOLO algorithm functions by partitioning the input image into an M×M grid, where each grid cell is tasked with object detection. The network is composed of 24 convolutional layers, which are then followed by two fully connected layers. This configuration generates an output tensor of size M × M × (N × 5+X), with N indicating the number of bounding boxes per grid cell and X representing the number of object categories. The final detection outcomes are derived by regressing the coordinates of the bounding boxes and calculating the class probabilities. Although YOLO excels in rapid object detection, its effectiveness diminishes for small object detection due to insufficient grid resolution, which can lead to multiple objects being assigned to the same grid cell. To address this limitation, YOLOv5 incorporates advanced data augmentation techniques such as extension, color space transformation, and mosaic augmentation through a data loader. Additionally, it leverages the anchor mechanism from CNN to enhance its capability in detecting small objects using a multi-scale approach, thus increasing its adaptability to various image sizes. Combining YOLOv5 with CNN, a fast small object detection system has been developed, specifically designed for accurately detecting and recognizing small targets in remote sensing images[13].

This ability to accurately detect and recognize small targets in remote sensing images can be utilized to identify a variety of objects on the road, including vehicles, pedestrians, traffic signs, traffic lights, animals, barricades, and more. This information is crucial to the environmental perception of autonomous vehicles. Identify vehicles around you and determine their speed and direction to make driving decisions such as changing lanes, speeding up, or slowing down. Autonomous driving systems will use a variety of sensors (such as lidar, radar, cameras, etc.) to acquire environmental information. YOLO can work with data from these sensors to provide a more comprehensive and accurate perception of the environment.

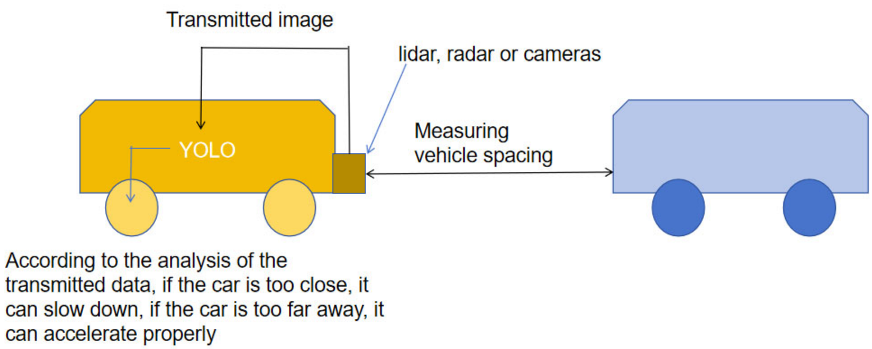

Fig. 1.YOLO model application in control the vehicle distance

As shown in **Fig. 1**, The car receives data signals through lidar, radar, and camera, and then transmits the image data to the YOLO system for processing, and the YOLO judges the distance of the car for speed regulation.

The in-car speech dialog system can reduce the time when the driver takes his eyes off the road by directly talking to the car AI to achieve certain actions such as adjusting the volume of the car stereo, adjusting the air conditioning temperature, and choosing a new route. This system greatly facilitates the driver's control of the car.

The SDS system is the result of the development of AI and natural language processing (NLP), and it features a system-directed conversation utilizing predefined menu choices.

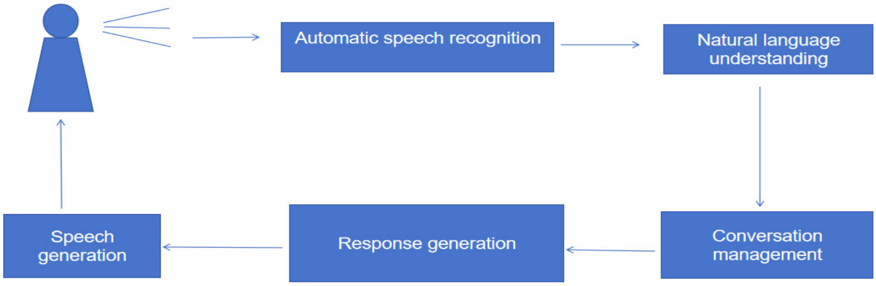

Fig. 2. Workflow of the five core modules of SDS

As shown in **Fig. 2**, this is a voice interaction process where the driver initiates commands or queries. These inputs are converted to text through automatic speech recognition. The text is then interpreted for intent using natural language understanding. Subsequently, the conversation management system determines appropriate responses or actions. The generated response text is converted back to natural speech using speech generation, which is then returned to the driver, completing the interaction loop.

SDS typically involves several key modules to process and respond to spoken inquiries. When a customer speaks, their voice is captured and converted to text by an automatic speech recognition module. The text is then processed by a natural language processing (NLP) engine. The engine extracts semantic content, including conversation behavior, object, and purpose. The dialog manager plays a crucial role by maintaining the conversation context, synchronizing external components, and making context-based decisions. For generating responses, the system often uses templates with placeholders that are filled with relevant entities. Finally, the response is converted back into speech by the speech generation module. This multi-step process, which may involve several conversational turns, is designed to ensure accurate and satisfactory interactions[14].

CNN is one of the most popular and commonly used deep learning networks. The primary advantage of CNN over its predecessors lies in its ability to automatically recognize pertinent features without the need for human supervision[15]. This technology can be used to detect quality problems in automotive parts, such as surface defects, dimensional deviations, etc.

By leveraging local connectivity and weight sharing, CNN can capture spatial hierarchies in images, making them well-suited for tasks like object recognition and scene understanding. The combination of convolutional layers, sub-sampling layers, and fully connected layers allows CNN to extract meaningful features from images and make accurate predictions[16].

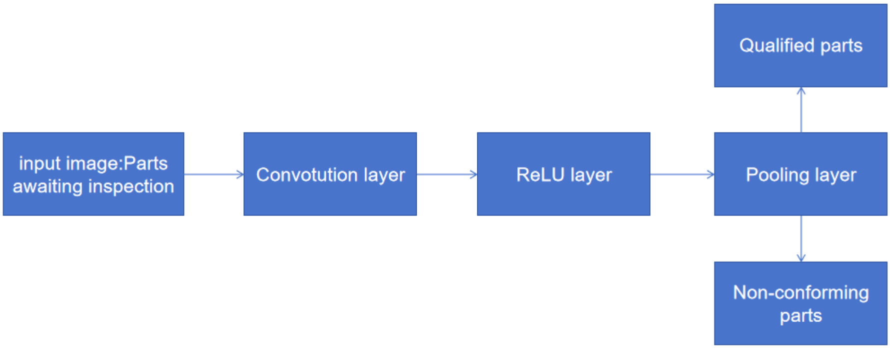

Fig. 3. The process of CNN inspection parts

As shown in **Fig. 3**, input the image first. The Convolution layer applies filters to the input image to extract features like edges, textures, or patterns. The Rectified Linear Unit layer introduces non-linearity by applying the activation function ReLU to the output of the convolution layer, helping the network learn complex patterns. The pooling layer reduces the spatial dimensions of the previous layer, which helps in controlling overfitting and also makes the network more computationally efficient. Finally, the defects are classified.

3.2 3D printing technology

The following will detail the process of 3D printing technology such as SLM used to manufacture vehicle parts. SLM is a 3D printing technique whose process involves using the heat energy of a laser beam to melt a metal powder. The melted powder is cooled, solidified, and finally formed layer by layer to form the desired three-dimensional structure. It can print out parts with only a few brackets without using abrasive tools. Brackets are often used to prevent parts from collapsing due to excessive laser scanning and to suppress warping problems caused by part cooling[17].

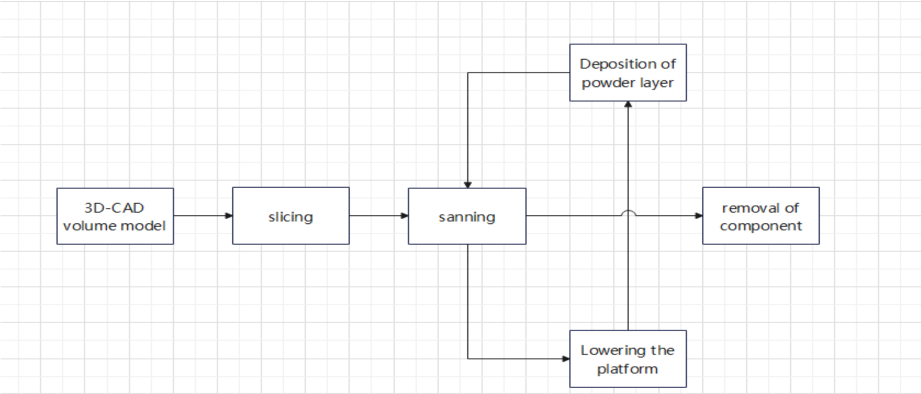

Fig. 4. The process of SLM technical printing

As shown in **Fig. 4**, first of all, modeling software is used for modeling, and then import printing software for slicing and layering. Laser scanning is heated to melt, the platform is lowered, after which the powder layer is deposited, and the laser scanning step is repeated. Disassemble the components until the machining is complete. Finally, removing the components.

SLM enables the production of a variety of complex automotive components. This technology is highly beneficial in manufacturing engine parts such as cylinder heads with intricate cooling channels, lightweight pistons, and optimized turbocharger blades. It also excels in producing robust transmission system components like intricate gears and housings, and lightweight drive shafts. SLM is advantageous for creating suspension system parts, including control arms with complex geometries and durable shock absorber components. Additionally, it is used to fabricate high-performance braking system parts such as brake calipers and discs, as well as exhaust system components like optimized exhaust manifolds and catalytic converter housings.

In terms of automobile structure, it is necessary to choose a material with lightweight and high strength for the body of the car. Below is a comparison of several common car body materials.

Table 1. Compare the advantages and disadvantages of some materials commonly used in automobile shell.

Materials	Advantage	Shortcoming
Aluminum	Light weight Corrosion resistance Recyclability Good thermal and electrical Conductivity	Higher cost Low strength and rigidity
Steel	High strength and rigidity Low cost Tractability	High strength and rigidity Low cost tractability
Carbon fiber	As light as a feather High strength Corrosion resistance	Extremely high cost Complex manufacturing process Greater brittleness

Compared to **Table 1**, aluminum as a 3D-printed car shell material is very advantageous, although its strength, and stiffness may not be as good as steel. It is better in the quality of light and can be enhanced by post-processing to enhance its surface strength and stiffness. Carbon fiber is fine as a car shell, but it cannot be used as a material through 3D printing, and its high production costs cannot be ignored. In contrast, aluminum can be printed with SLM technology, which can meet the needs of the car shell with more design possibilities. Aluminum is a good material for 3D printing cars.

For aluminum automotive components printed with SLM, effective post-processing methods include laser polishing, sandblasting, chemical etching, and thermal treatments like annealing and heat treatment. These methods improve surface quality, microstructure, and mechanical properties. Studies suggest that a combination of techniques, such as steady and pulsed laser scanning methods, along with treatments like Hot Isostatic Pressing (HIP), abrasive blasting, and chemical engraving, can enhance fatigue resistance and overall performance. Additionally, the use of recycled powder and careful control of thermal post-processing parameters have shown promise in improving material uniformity and reducing costs[18].

In addition to the use of SLM technology, it is also possible to achieve energy saving and emission reduction by printing some environmentally friendly polymers and composite materials. Using PLA to make auto parts is one of them[19].

According to Ivey et al's experiments on extrusion-based additive manufacturing using carbon fiber-reinforced PLA filaments, PLA demonstrates favorable characteristics for the extrusion-based 3D printing process when the fiber content is 14%-16%[20]. Additionally, research conducted by Rodriquez et al, which utilized specimens produced from Acrylonitrile Butadiene Styrene(ABS) and PLA through FDM additive manufacturing, demonstrated that PLA specimens exhibit notable rigidity, enhanced tensile strength, and robust interlayer bonds[20]. Therefore, PLA meets the needs of automotive parts in terms of performance.

Among the thermoplastic aliphatic polyesters, PLA is made from rice, corn, and sugar beets as a raw material. PLA is nontoxic, has strong renewability, and is more compatible than other biodegradable polymer materials[21].

PLA can be used to manufacture several automotive components, including interior accessories (such as dashboard panels and door handles), exterior parts (such as trim strips and lamp housings), custom parts (such as exclusive emblems and body stickers), functional parts (such as seat adjustment devices and cup holders), and auxiliary tools (such as customized wrench and caliper brackets). Combined with the previously described non-toxicity and easy regeneration and degradation of PLA, it will make it popular in 3D printing environmentally friendly cars.

4 Application

4.1 3D part defect and shape analysis

Before 3D printing, design optimization and shape analysis can improve printing efficiency and material utilization. Through detailed feature extraction and analysis of design graphics, CNN helps to optimize the design structure and improve the printing effect.

Here is an experiment, ‘Deep learning-based in-situ monitoring of additive manufacturing processes: A convolutional neural network approach’, that demonstrates the combination of CNN and 3D printing technology. This experiment aims to develop a deep learning-based method for detecting and identifying defects in real time during 3D printing.

The experiment used an industrial equipment Concept M2, and the SLM process of stainless steel powder was carried out. The apparatus is outfitted with a continuous mode fiber laser that operates at 1071 nm wavelength, beam quality $M^2 = 1.02$, and spot size 90 μm. One fiber Bragg grating (FBG) sensor was also added to Concept M2 to detect airborne acoustic emission（AE） signals produced during Additive manufacturing（AM）.

The experiment involves collecting acoustic data during the manufacturing of a particular work-piece, and adjusting machining parameters to create cross-sections of different qualities. Samples were prepared using a line-by-line scanning strategy, and optical inspection classified regions based on different scanning speeds. Standard wavelet packet transform extracted frequency band features, used as inputs for an SCNN classifier trained and tested in Microsoft Visual Studio C#. Results showed varied defects due to different laser scanning parameters[22].

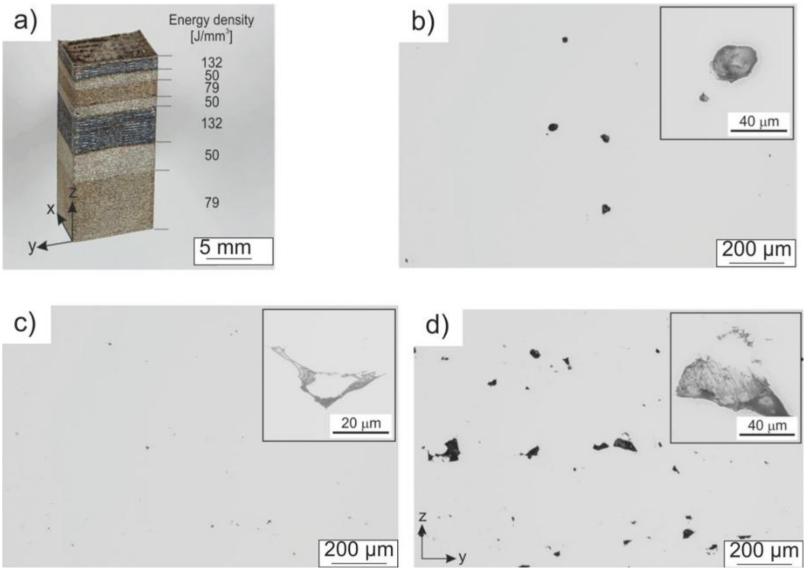

Fig. 5.Common defect[22]

As shown in **Fig. 5**, the figure displays an SLM test workpiece produced with three different energy densities: 50 J/mm^3 for white regions, 79 J/mm^3 for deep yellow regions, and 132 J/mm^3 for blueish regions. The insets depict common flaws observed: tubular defects b) with 132 J/mm^3 which is medium quality, small lack-of-fusion faults c) with 79 J/mm^3 which is high quality, and large lack-of-fusion faults d) with 50 J/mm^3 which is poor quality. The directions z and y match up with a)[22].

Overall, the experiment enabled real-time defect monitoring and classification in 3D printing through acoustic data and deep learning.

4.2 3D printing real-time quality inspection and monitoring

In the 3D printing process, real-time monitoring and quality inspection are important links to ensure the accuracy and quality of printed parts. YOLO and CNN models can be used to identify defects or errors in the printing process, such as problems with stratification, faulting, under-extrusion, or over-extrusion. The following is an experimental case about checking parts defects with the YOLO model.

In real production, four types of faults have been identified in darning needles: wringing, length size mistakes, endpoint size errors, and crooked forms[23]. The experiment used a high-speed industrial camera on a platform designed for real-time object detection in an industrial setting, the 0.8 cm darning needle dataset was collected while the object was in motion[23]. The camera was positioned 10 centimeters away from the conveyor belt. The experimenter gathered the dataset using over 3000 images, with over 2000 designated for training and over 800 for testing.

These images were captured with continuous adjustments to the positions of the detection objects. The training images contained more than 6000 darning needle labels, while the testing images included more than 2000 labels.

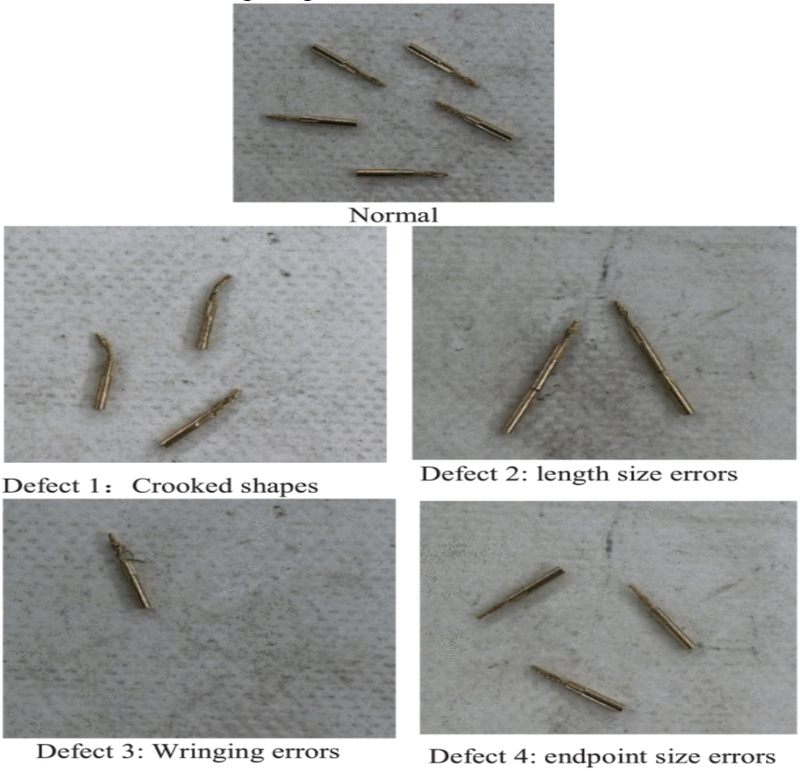

Fig. 6. Example of autonomously collected experimental data[23]

As shown in **Fig. 6**, normal darning needles and four common defects are shown.

To improve the ability of a system to maintain stable and efficient performance under different conditions of the algorithm without reducing the detection accuracy, the common method that researchers tend to use is data enhancement[23]. Researchers usually choose Horizontal flipping, translation, chopping, and color dithering to enhance experimental data[24]. Five rotation angles from 0° to 90° were used to enhance the image data to prove the universality of the model in all directions. The details regarding the number of labels for each category in the original data, augmented data, and new data are summarized in **Table 2**.

Table 2. Comparison label information of 0.8cm darning needle data before and after enhancement[23]

Data	Original	Augmentation	New data	
Defect	Train	Train	Train	Test
Normal	1261	600	1861	400
Defect 1	1258	600	1858	400
Defect 2	1239	600	1839	400
Defect 3	1246	600	1846	400
Defect 4	1302	600	1902	400
Total	6306	3000	9306	2000

After a series of data processing with the YOLO model, the following is the final result.

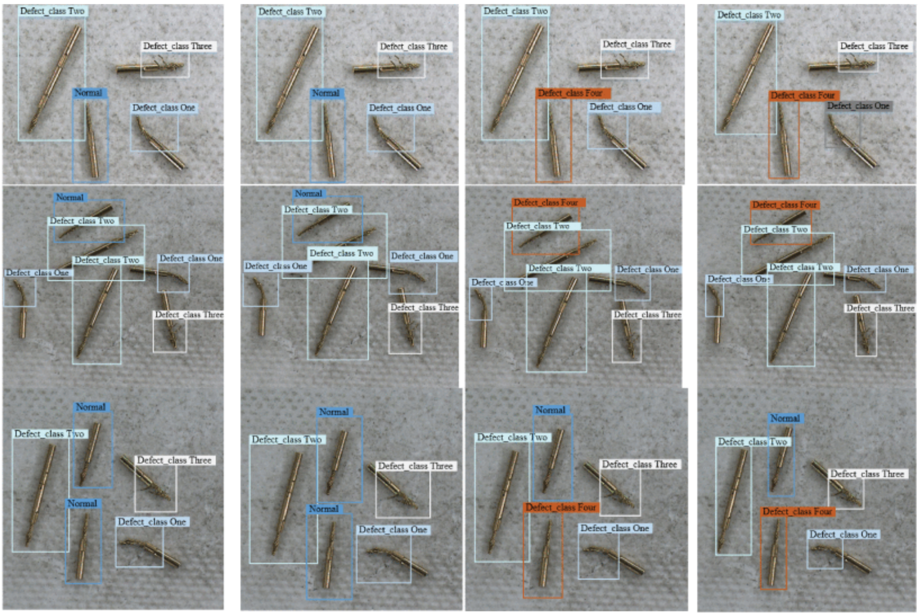

Fig. 7.Experimental model processing results[23]

Fig. 7 shows the sample used for defect detection and the test results. After comparison with the real situation, the experiment shows that this method can detect and distinguish 4 kinds of defects well.

This highlights the superior performance and potential applicability of the YOLO model in defect detection tasks, especially in scenarios where detecting small-scale anomalies is critical to ensuring product quality and safety. I think this is a good experimental example to prove that the YOLO model can be used for real-time quality inspection and monitoring of 3D printing.

5 Conclusion

Based on the current complex environmental background, this paper proposes the application of AI and 3D printing technology to energy-efficient vehicles. In terms of AI, the YOLO model is applied as the basis of the autonomous driving system. The SDS system is used to achieve human-vehicle language communication to achieve some convenient operations, and the CNN system is used to detect and check the 3D-printed vehicle parts. In terms of 3D printing, aluminum can be printed as a car body with SLM technology, and some PLA auto parts can be printed with FDM technology. In the following, the case experiments of detecting parts defects with the CNN model and YOLO model are introduced respectively.

In the future, technology will continue to develop rapidly. So far, the AI model YOLO has been ineffective in dealing with complex surroundings. However, YOLO will be upgraded with a more accurate and rapid identification ability to realize the automatic driving system in the future. The SDS system may be integrated into Chat GPT to make human-computer interaction more convenient and real. There may also be simpler and faster methods for the inspection of automotive parts. In the field of 3D printing, carbon fiber printing may be realized in the future so that 3D printed cars can be integrated, more environmentally friendly and convenient.

Combining YOLO models, SDS systems, and 3D printing technology with the automotive industry is expected to push the automotive industry towards a more sustainable and efficient direction.

YOLO models can give vehicles more intelligent perception and decision-making capabilities, helping vehicles to sense various objects in the surrounding environment in real-time, including other vehicles, pedestrians, bicycles, etc., thereby improving vehicle safety and autonomous driving capabilities. The SDS system enhances the driver and passenger experience by allowing the driver to control the air conditioning temperature, volume level, and route selection and reduce distractions through speech. In the process of optimizing vehicle design and manufacturing, the CNN system can be used to detect part quality. And 3D printing technologies, such as SLM and FDM, can make automotive manufacturing more flexible and efficient. SLM technology can be used to print lightweight aluminum car housings, thereby reducing vehicle weight, improving fuel efficiency, and helping to reduce carbon emissions. FDM technology can be used to print auto parts, such as PLA auto parts, with advantages such as low cost and short production cycle, which helps to reduce the cost and resource consumption of automobile manufacturing.

Through lightweight design and customized production, cars can be more energy-efficient and environmentally friendly, reducing energy consumption and emissions. This is of great significance for reducing carbon footprint and environmental pollution. At the same time, intelligent perception and decision-making systems can optimize the operational efficiency of vehicles, avoid unnecessary energy waste, and make cars more environmentally friendly and sustainable.

The application of combined artificial intelligence and 3D printing technology will accelerate the pace of technological innovation and development in the automotive industry. This can not only improve the performance of existing vehicles but also lay the foundation for the construction of smart transportation and smart cities in the future.

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