

Deep learning retrieval of 3D casting models combined with professional knowledge for process reuse

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Abstract: Accurate retrieval of casting 3D models is crucial for process reuse. Current methods primarily focus on shape similarity, neglecting process design features, which compromises reusability. In this study, a novel deep learning retrieval method for process reuse was proposed, which integrates process design features into the retrieval of casting 3D models. This method leverages the comparative language-image pretraining (CLIP) model to extract shape features from the three views and sectional views of the casting model and combines them with process design features such as modulus, main wall thickness, symmetry, and length-to-height ratio to enhance process reusability. A database of 230 production casting models was established for model validation. Results indicate that incorporating process design features improves model accuracy by 6.09%, reaching 97.82%, and increases process similarity by 30.25%. The reusability of the process was further verified using the casting simulation software EasyCast. The results show that the process retrieved after integrating process design features produces the least shrinkage in the target model, demonstrating this method's superior ability for process reuse. This approach does not require a large dataset for training and optimization, making it highly applicable to casting process design and related manufacturing processes.

Keywords: casting; 3D model retrieval; process reuse; deep learning

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1 Introduction

Casting is crucial in industries such as aviation, aerospace, transportation, and shipbuilding, supporting the innovation of numerous products and high-end equipment. Typical castings, such as satellite brackets, missile shells, engine casings, and aerospace engine

blades, feature complex structures like irregular surfaces, internal channels, and structural holes, making process design highly challenging and time-consuming. In industrial manufacturing, over 75% of product designs are based on case studies^[1]. Reusing and refining mature processes from existing products can significantly shorten production cycles. However, current process reuse relies on manual retrieval of casting process cards, which is inefficient and dependent on experience^[2]. With the advancement of Industry 4.0 and digital intelligent manufacturing^[3,4], 3D model-based process design is widely adopted in casting enterprises^[5]. Thus, accurate retrieval of 3D models is essential for effective process reuse.

3D model retrieval methods are generally classified as text-based or content-based. Text annotation is labor-intensive and often fails to fully capture model's features, making content-based retrieval more popular^[6]. Content-based retrieval automatically identifies models

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based on geometric shape, topological structure, and other features, offering a more objective and comprehensive representation than text-based methods.

Content-based retrieval is primarily divided into shape-matching and data-driven methods [7]. The shape matching method calculates similarity by comparing shape descriptors of 3D models using tools like D2 shape distribution [8], 3D Zernike moment descriptor [9], Fourier descriptors [10], shape context [11], local surface descriptors [12], and Laplace-Beltrami spectra [13]. While these descriptors provide translation and rotation invariance, their accuracy is limited by descriptor density, which may result in loss of shape detail information, particularly for complex 3D casting models during feature extraction [14].

Data-driven enhances efficiency by using objective data analysis to establish predictive models [15, 16]. Data-driven methods for 3D model retrieval can be divided into two types: model-based and view-based. The model-based approach represents the 3D model as voxels [17], point clouds [18], or polygonal meshes [19], and then deep learning is used to extract features and perform similarity calculations, as seen in PointNet [20], VoxNet [21], and MeshNet [22]. Deep learning-derived shape features generally outperform traditional shape descriptors [23]. However, voxel-based methods require significant memory for complex casting models due to their high dimensionality and sparsity [24]. Point cloud-based methods use point coordinates in three-dimensional space but often overlook spatial structures like adjacency relationships [14]. Mesh-based methods depend on the resolution, regularity, and uniformity of the grid.

Due to the easy acquisition and high distinguishability of 2D views of 3D models [25], and the success of deep learning in 2D image feature extraction, 3D model retrieval based on 2D images has shown advanced performance [26-28]. Leveraging mature deep learning models like AlexNet [29], VGGNet [30], and ResNet [31], pre-trained on large-scale image datasets, further enhances efficiency. For instance, the multi-view convolutional neural network (MVCNN) [32] projects a 3D model onto a 2D plane from multiple angles to extract and fuse features such as shape and texture. Additionally, Nie et al. [33] represented 3D model features through a 2D panoramic view. Although view-based methods are more efficient than model-based ones, they may lose three-dimensional information such as depth and internal structure [34, 35]. This loss is not significant for non-engineering parts but is crucial for engineering parts, which have features that affect subsequent forming or machining processes. For instance, in casting design, significant or uneven changes in wall thickness can lead to inconsistent cooling rates, resulting in deformation and shrinkage defects [36].

Furthermore, current 3D model retrieval methods for process reuse mainly focus on shape semantics, overlooking the process design features within the 3D model. Huang et al. [37] incorporated processing area features (e.g., geometric dimensions, volume, and area of holes and lug boss) into the retrieval index, achieving an accuracy rate of 82%. Guo et al. [7] included

pressure distribution information from injection positions in plastic injection molding, resulting in an accuracy rate of 86.61% compared to 78.57% using only shape distribution. These studies highlight the importance of manufacturing process-related information in 3D model retrieval for process reuse. Therefore, for effective reuse of casting processes, it is crucial to develop a comprehensive 3D model retrieval system that includes shape features, internal structural features, and process-related design features.

Based on this, a deep learning method for 3D model retrieval in casting that integrated three views, sectional view, and professional knowledge was proposed. CLIP model was employed to capture both external geometric shapes and internal structural details from three views and sectional views. Additionally, casting process design knowledge (PDK) was incorporated to obtain relevant features such as modulus, symmetry, average wall thickness, and maximum wall thickness. These features are fused with shape features to enable precise retrieval of casting models with similar processes. This approach aims to offer a new solution for reusing casting processes, supporting fast and accurate process decisions.

2 Methods

The process illustrated in Fig. 1 for feature construction and similar casting retrieval was adopted. This process includes four main stages:

- (1) Casting models standardization and view acquisition: Rotate all castings so that the longest edge aligns with the Z-axis, then obtain the front, left, top, and sectional views.
- (2) Geometric shape feature extraction: Combine the three-view and sectional images, use the Sobel operator for image sharpening, and extract features from the sharpened images using deep learning.
- (3) Process design feature acquisition: Calculate the modulus, symmetry, average wall thickness, and maximum wall thickness of the casting, and concatenate these with the deep learning-extracted features.
- (4) 3D model retrieval: Use cosine similarity to calculate the similarity between the fused features and those of other castings in the database, and sort the results to find the castings with the highest similarity.

2.1 Casting 3D model database

The 3D model database includes 230 casting models such as automotive hubs, car doors, engine casings, control valve bodies, pump bodies, complex shell casings, and propeller blades, in stereolithography (STL) file format. Figure 2(a) shows examples from this database. Although shape features can distinguish between different categories, selecting castings with reusable processes from those with similar shapes is challenging. To ensure process reusability among these similar castings, additional PDK is needed. The dimensions of castings were scaled by a factor of $100/D_{\max}$ (where $D_{\max}$

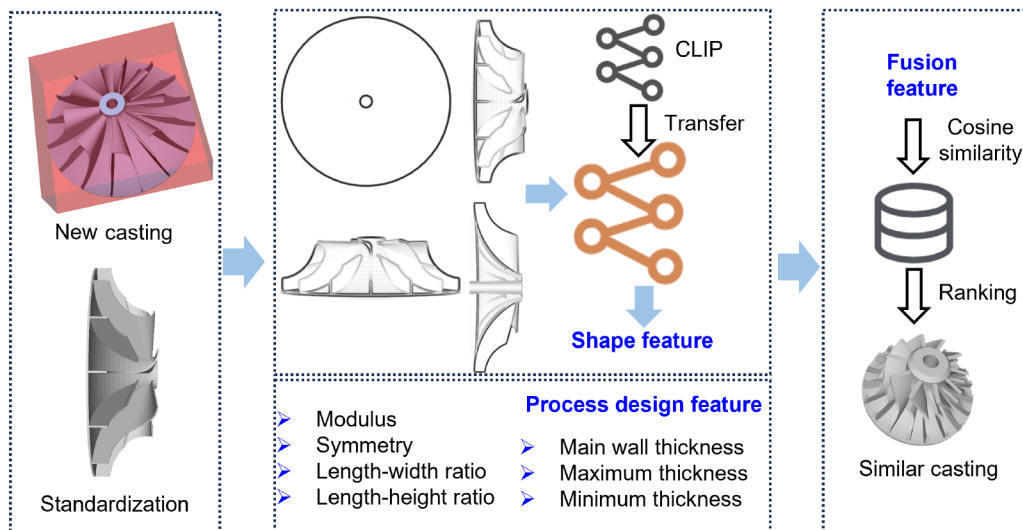


Fig. 1: Flow chart of deep learning retrieval of 3D casting models combined with professional knowledge

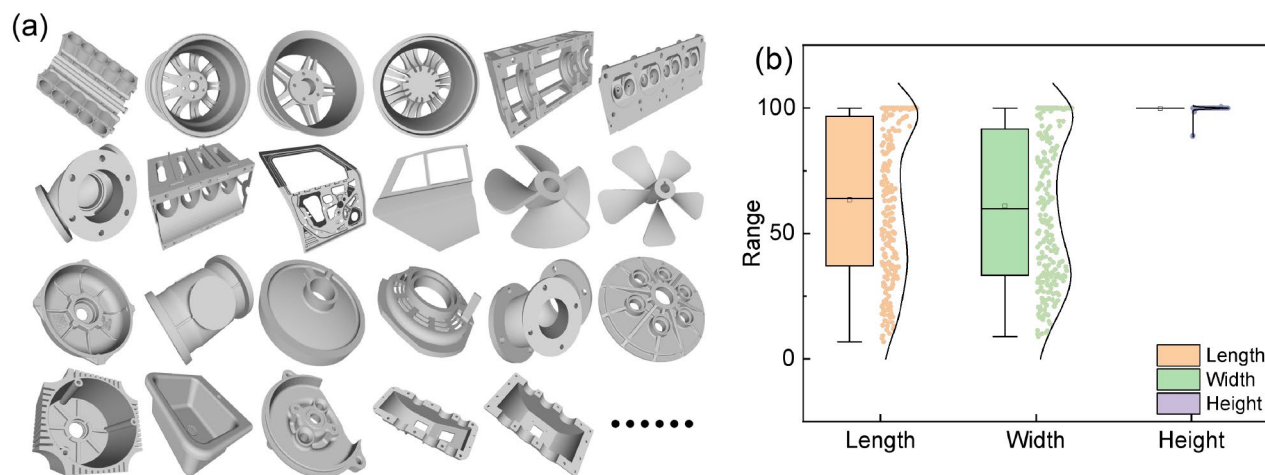


Fig. 2: Examples in the 3D model database of castings (a) and distribution of casting dimensions (b)

is the maximum value of length, width, or height) to ensure both the casting database and query castings are comparable, with a maximum size of 100 cm. This scaling preserves the original length-to-width-to-height ratio. The distribution of casting dimensions after scaling in the casting model database is shown in Fig. 2(b), revealing a wide size range with noticeable variations.

2.2 Casting models standardization and shape feature extraction

The varying spatial positions and orientations of 3D models result in poor comparability of the obtained 2D views, necessitating the standardization of model postures. In this study, the longest edge of the 3D model was aligned along the Z-axis, considering that similar models typically have similar dimensions. Firstly, the smallest oriented bounding box (OBB) was generated around the casting model to identify the maximum values of the length, width, and height of the bounding box to obtain its longest edge. Then, align the longest edge with the Z-axis and rotate it to be perpendicular to the horizontal plane, as shown in Fig. 3. After standardization, the front view (opposite X-axis), left view (positive Y-axis),

top view (opposite Z-axis), and section view (opposite X-axis) of the 3D model were captured. To represent the internal structures of cylindrical and other complex models, a vertical plane at half the X-axis length as the cutting plane was selected and the resulting front cross-sectional view was used. The three views and cross-sectional view images were grayscale, with a resolution of 300×300 in PNG format. Research indicates that the three views can effectively represent 3D models in retrieval tasks, as each view offers distinct shape information^[38, 39]. While incorporating additional perspectives, such as in MVCNN^[32], can enhance detail, it also increases model complexity and introduces potential redundancy. To balance the information from different angles and prevent overemphasis on a single perspective that could skew the model's judgment, only one cross-sectional view was selected. Although this may reduce shape information, the process design features help compensate for information loss. To eliminate interference from the triangular lines in STL files (as shown in Fig. 4), the rendered images were used to present the 2D view of the casting, providing a clearer representation of its shape. The Python version of VTK library was applied to read and render STL files without additional rendering, such as

profile enhancement or smooth shading. These 2D views were then combined in the sequence of left, front, top, and section views, as shown in Fig. 3. Given that 2D views primarily convey shape features, and that image preprocessing enables convolutional neural networks to extract more effective and reliable features^[40], the Sobel operator was applied^[41] to sharpen the edges of the 2D views, as shown in Fig. 3.

After standardization, the 2D views of the casting model

display distinguishable features. The Sobel operator enhances these features, making contours and shapes clearer and easier to compare, facilitating the identification of the casting model. However, standardizing by placing the longest edge on the Z-axis still results in pose differences. For instance, wheel hub models in Figs. 3(b) and (c) show significant shape differences in the left view due to posture variations, despite their overall similarity. Convolutional neural networks

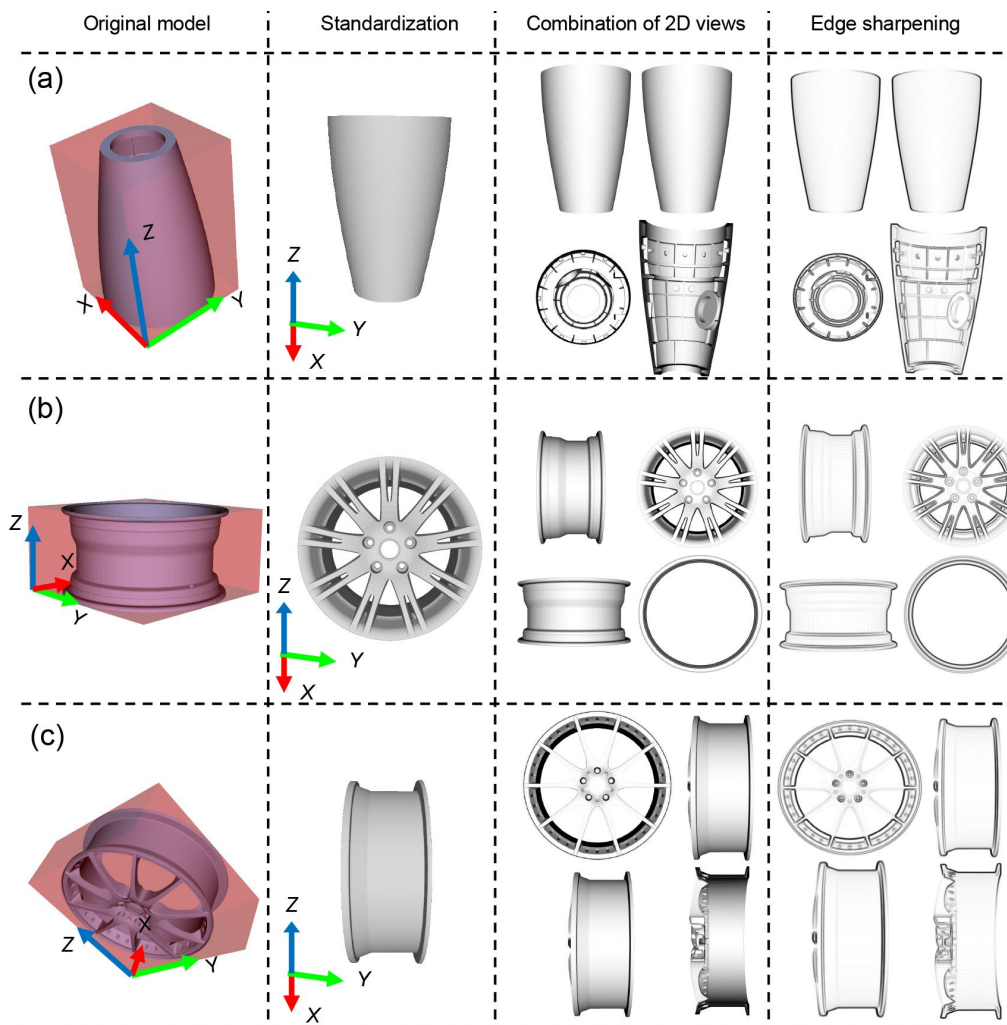


Fig. 3: 3D models of castings with different spatial positions before and after standardization, and 2D views before and after edge sharpening: (a) cylindrical casting; (b) horizontal wheel hub; (c) tilted wheel hub

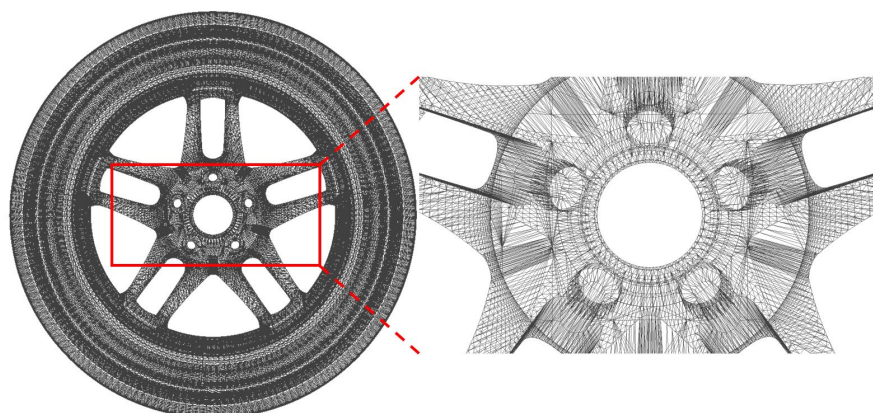


Fig. 4: Wireframe diagram of wheel hub castings in STL file format

(CNNs), with a certain degree of translation invariance and rotation invariance, are adept at extracting effective image features^[42]. Recent advancements in CNN architectures, such as AlexNet^[29], VGGNet^[30], GoogLeNet^[43], and ResNet^[31], have proven successful. In this study, VGGNet16 and ResNet50 were selected. However, for casting model retrieval with no labels and limited data, traditional CNN architectures may not be sufficient. Therefore, dual-stage implicit object-oriented network (DINOv2)^[44] and CLIP^[45] were incorporated. DINOv2, a self-supervised learning method, addresses label scarcity by learning relationships between images without labels, enhancing model generalization. It uses a self-attention mechanism to capture global and local features effectively. CLIP, trained on large-scale datasets using contrastive learning, provides universal semantic knowledge and image feature representation, offering zero-shot capability. The above models were obtained through model transfer. The spliced image was resized to 224×224 before being input into above models. Additionally, traditional image feature extraction methods such as Scale-Invariant Feature Transform (SIFT)^[46], oriented fast and rotated binary robust independent elementary features (ORB)^[46] and Gray Level Co-occurrence Matrix (GLCM)^[47] were compared to identify the optimal retrieval model.

2.3 Process design feature acquisition

To achieve shape similarity while ensuring process similarity, this study introduced professional knowledge-based process design features, including modulus, main wall thickness, average wall thickness, maximum wall thickness, minimum wall thickness, symmetry, length-to-width ratio, length-to-height ratio, and width-to-height ratio. The process design features are directly extracted using Python and the Trimesh library.

The modulus directly affects the solidification mode and potential defects of a casting. It is calculated using Eq. (1)^[48]:

$$M = \frac{A}{V} \quad (1)$$

where M is the modulus (cm), V is the casting volume (cm³), and A is the casting's heat dissipation surface area (cm²). The significance of the modulus lies in its ability to predict solidification time for castings of various shapes, weights, and purposes, castings with equal modulus will have similar solidification time. Castings with a small modulus solidify quickly, which can cause rapid surface solidification and form a hard shell, potentially leading to defects like cold shuts. Conversely, castings with a high modulus solidify slowly, increasing the risk of shrinkage or porosity. To simplify calculations in this study, the overall modulus was determined using the total volume and surface area of the casting's 3D model.

The pouring time, filling time, and pouring system design are closely related to wall thickness. The appropriate pouring time for sand casting was determined by Eq. (2):

$$t = f \left(\sqrt{G} + \sqrt[3]{\frac{1}{5} \delta \cdot G} \right) \cdot \left(\frac{2}{3} \right)^{n-1} \quad (2)$$

where t is the appropriate pouring time, f is the material coefficient, G is the casting weight (kg), δ is the main wall thickness (mm), and n is the number of pouring system components. The number of vertical cylinders in differential pressure casting was calculated by Eq. (3):

$$m = \frac{(0.016 - 0.028)S}{\delta} \quad (3)$$

where m is the number of vertical cylinders, S is the circumference of the casting's outer shape. Wall thickness significantly impacts the solidification process and final quality of castings. Areas with larger wall thicknesses solidify slower, leading to potential shrinkage. To compensate, risers or chill may be needed to prevent shrinkage cavities and porosities. Castings with uneven wall thicknesses might require complex solidification control strategies, such as local cooling or heating adjustments to manage solidification rates and shrinkage behavior. In this study, wall thickness was obtained using the thickness (mm) function in the Trimesh library, with the main wall thickness defined as the mode of the measured wall thicknesses.

Symmetry in a casting refers to its geometric regularity, simplifying both the gating system and mold design compared to asymmetric counterparts. This characteristic also facilitates more accurate predictions of cooling and shrinkage, as all parts of the casting respond similarly to temperature changes. For symmetrical castings, center pouring evenly distributes molten metal from the center to all areas, promoting uniform cooling and reducing internal stress. Conversely, asymmetric castings often require more complex gating systems^[49, 50]. Symmetry significantly influences casting complexity, which is crucial for process design considerations. For instance, in low-pressure casting, the filling pressure is determined by Eq. (4):

$$P = \frac{H\rho K}{10200} \quad (4)$$

where P is the pressure needed to fill the mold cavity (MPa), H is the rise height of the metal in the mold (cm), ρ represents the density of the metal (g·cm⁻³), and K is the filling resistance coefficient ranging from 1.0 to 1.5. When a casting is complex with thin walls, the high filling resistance results in a correspondingly high K value.

In this study, symmetry calculations were performed using the methodology outlined in Fig. 5. The calculation principle is that if the casting is symmetrical, the two sub-models obtained by cutting along the symmetry plane will be identical, and the same rays will pass through each sub-model at equal distances. In this study, the model was divided along the Y - Z , X - Z , and X - Y planes, resulting in two sub-models for each division. For each sub-model, 500 rays were emitted from a plane parallel to the symmetry plane (Planes P_a and P_b in Fig. 5) and the length of each ray passing through the sub-model was calculated. The specific calculation is given by Eq. (5):

$$YD_i = 2_i - 1_i + 4_i - 3_i + \dots + N_i - (N-1)_i \quad (5)$$

where YD_i represents the distance that the i -th ray, parallel to the X - Z plane and directed positively along the Y -axis, penetrates the model, and N_i is the coordinate of the N -th

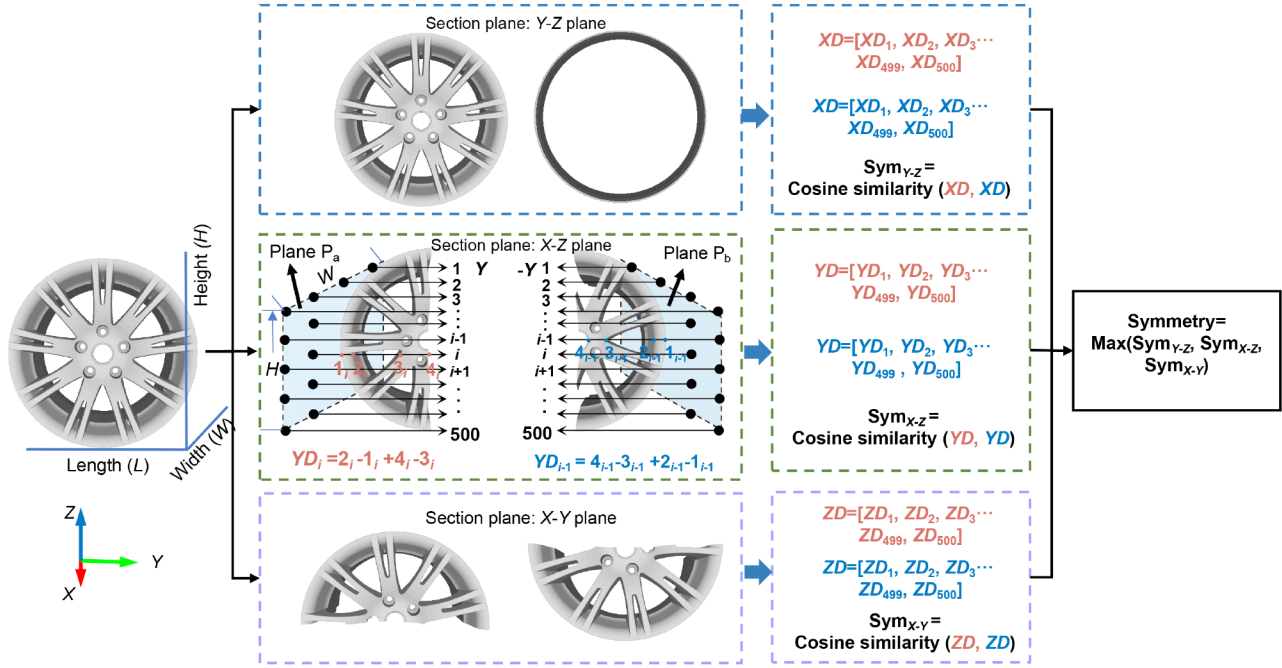


Fig. 5: Calculation process for symmetry of castings

intersection point between the i -th ray and the model. After obtaining the distances of 500 rays penetrating the two sub-models, the similarity between them was calculated using cosine similarity. The equation for cosine similarity is as follows:

$$\text{Similarity}(A, B) = \frac{A \cdot B}{\|A\| \times \|B\|} = \frac{\sum_{i=1}^n (A_i \times B_i)}{\sqrt{\sum_{i=1}^n A_i^2} \times \sqrt{\sum_{i=1}^n B_i^2}} \quad (6)$$

where A and B are two n -dimensional vectors. The symmetry of the model about the Y - Z , X - Z , and X - Y planes is determined, and the maximum value among these symmetries is taken as the overall symmetry of the model.

The aspect ratios of castings can significantly influence the flow characteristics of molten metal entering the mold. A larger aspect ratio can increase the flow distance of the molten metal, affecting its fluidity and filling capability. This might necessitate designing a more effective pouring system, such as increasing the number of gates or altering gate positions, to ensure the molten metal can evenly and fully fill the mold cavity. Additionally, the aspect ratio of castings is a factor in determining their complexity. In this study, length-to-width ratio is defined as the ratio of the length in the Y -axis direction to the X -axis direction, length-to-height ratio is the length in the Y -axis direction to the Z -axis direction, and width-to-height ratio is the length in the X -axis direction to the Z -axis direction. After calculating the process design features, the architecture of the model is depicted in Fig. 6 for clarity.

2.4 Feature filtering and mergence

To reduce the model's complexity and enhance generalization, process design features were screened using the Pearson correlation coefficient. The calculation equation for the Pearson correlation coefficient is as follows:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (7)$$

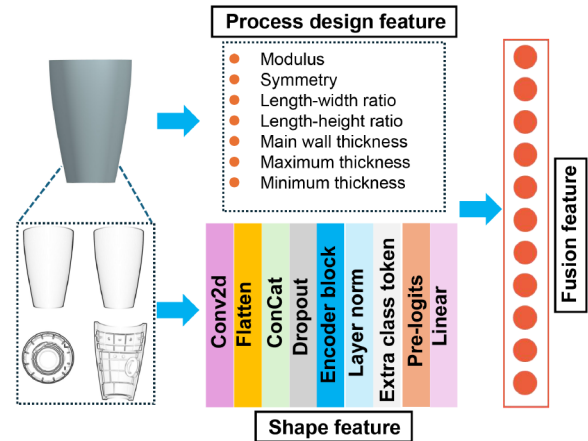


Fig. 6: Specific architecture of the model (taking CLIP model as an example)

where r is the correlation coefficient, x_i and y_i are the i -th values of two n -dimensional vectors, and $\bar{x}$ and $\bar{y}$ are the means of the two vectors, respectively.

The selected process design features were combined with shape features to derive a comprehensive feature set for calculating the similarity of different casting models. The similarity between these fused features and other castings in the database was then calculated using cosine similarity. The castings were subsequently ranked by similarity to identify those with the highest similarity.

3 Results

The correlation coefficients between process design features of all castings in the database are shown in Fig. 7. There is a strong relationship between the average wall thickness and the main wall thickness of the casting due to their similar statistical characteristics. Additionally, the average wall thickness and

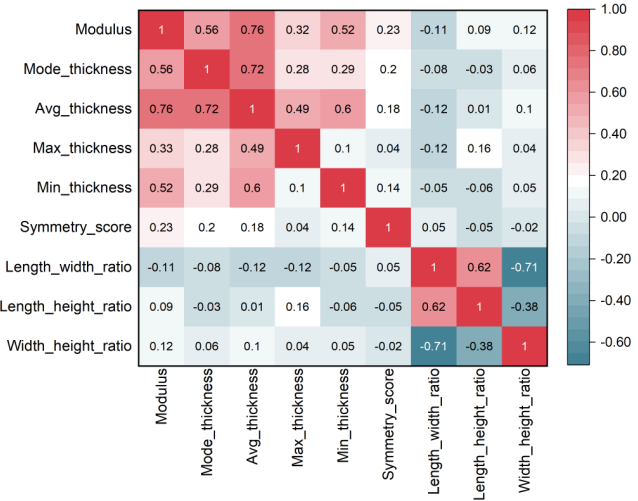


Fig. 7: Heat map of correlation coefficients for process design features

the modulus are highly correlated because the overall modulus is calculated using the total volume and surface area of the casting, which closely aligns with the average wall thickness. There is also a clear correlation between the aspect ratios of the castings, as these ratios involve the same dimensional attributes. Using a threshold of 0.7 for feature selection, average thickness and length-to-width ratio were removed from the process design features. The distribution of the screened process design features is shown in Fig. 8, indicating no significant correlation between the remaining features and demonstrating the diversity of the castings.

Wheel hub castings and engine cylinder block castings were used to demonstrate the retrieval performance of different models. Table 1 and Table 2 present the retrieval results for wheel hub castings and engine cylinder block castings, respectively, without incorporating PDK. Traditional image feature extraction methods like SIFT and ORB, as well as

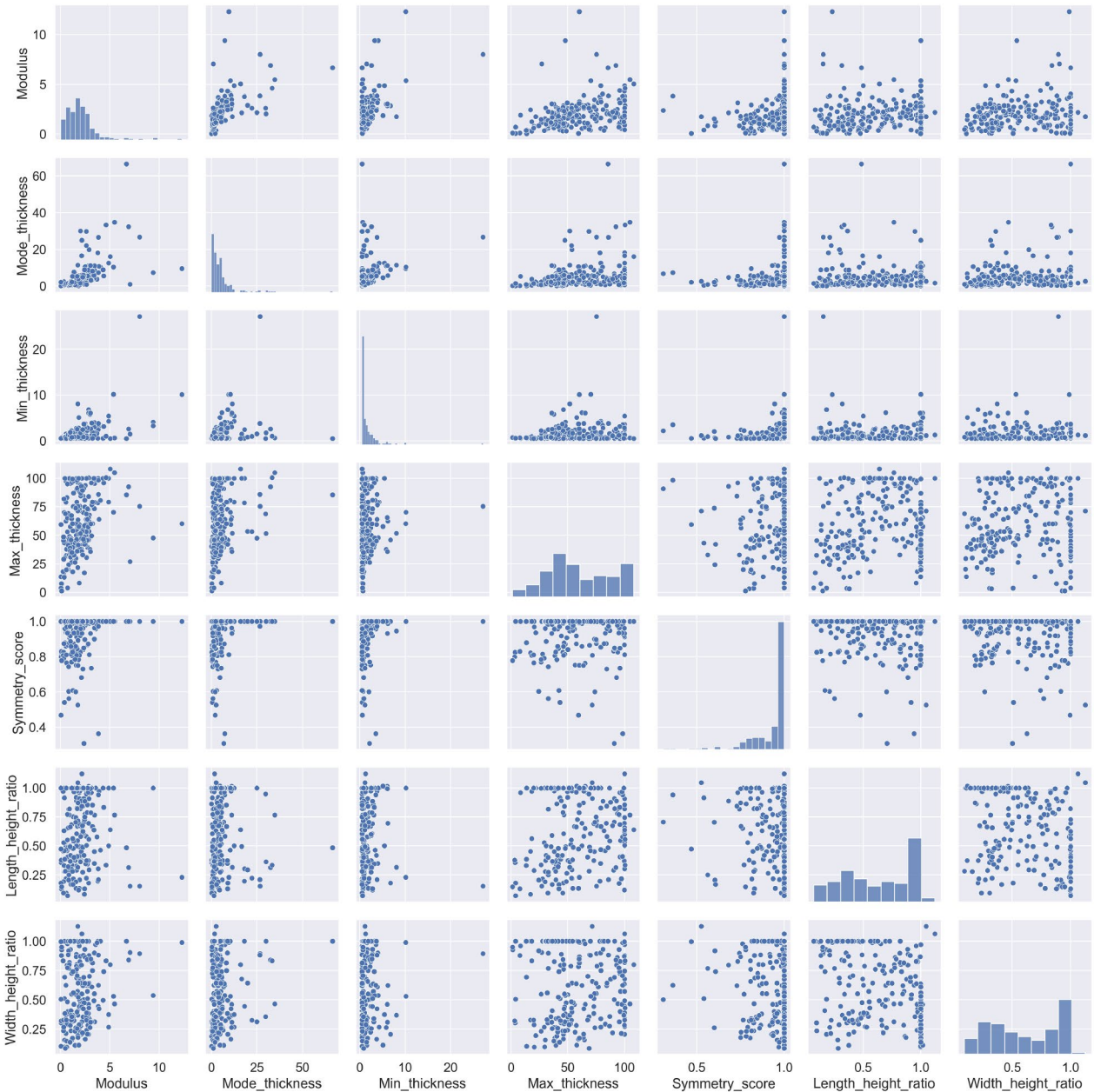


Fig. 8: Distribution map of process design features after feature selection

Table 1: Retrieval results for wheel hub castings without incorporating PDK

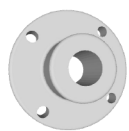
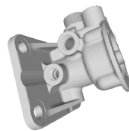
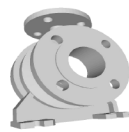
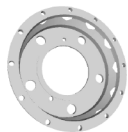
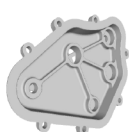
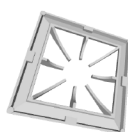
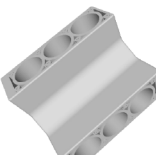
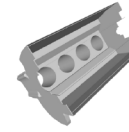
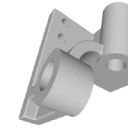
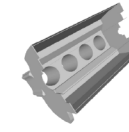
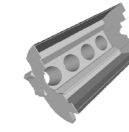
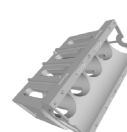
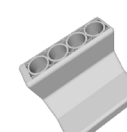
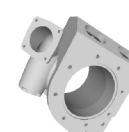
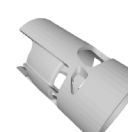
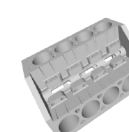
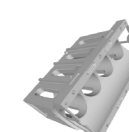
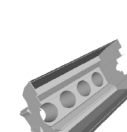
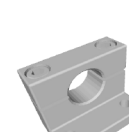
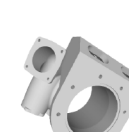
Query	Sorting	DINOv2	CLIP	SIFT	ORB	GLCM	VGG16	Resnet50
	A	 0.9590	 0.9612	 0.3221	 0.1465	 0.4508	 0.7877	 0.9152
	B	 0.9444	 0.9528	 0.3131	 0.1345	 0.4309	 0.7769	 0.9050
	C	 0.9316	 0.9325	 0.2997	 0.1284	 0.3992	 0.7695	 0.8978

Table 2: Retrieval results for engine cylinder block castings without incorporating PDK

Query	Sorting	DINOv2	CLIP	SIFT	ORB	GLCM	VGG16	Resnet50
	A	 0.9412	 0.9528	 0.2311	 0.1523	 0.2078	 0.7393	 0.9191
	B	 0.9389	 0.9401	 0.2236	 0.0545	 0.1682	 0.7070	 0.8976
	C	 0.9222	 0.9358	 0.2166	 0.0381	 0.1432	 0.6968	 0.8833

GLCM, show limitations in capturing the complex geometry and shape characteristics of 3D models. SIFT and ORB are typically used for key point detection and description in natural images, while GLCM focuses on texture information based on image grayscale, which may not fully capture the shape and structure information of images. In contrast, deep learning models such as VGG16 and ResNet50 perform better, as they can learn rich visual features from images. However, for complex engine cylinder blocks, VGG16 and ResNet50 do not achieve accurate retrieval results. This is because the parameters obtained through model transfer are not fully applicable to the 2D image feature extraction of casting models. These models require a large amount of labeled data for training and parameter optimization to obtain reliable generalization ability. The DINOv2 and CLIP models

outperform the other methods. These models encode images into vector representations in the semantic space, capturing both the visual features and the semantic hierarchy of the images. This indicates that semantic features may play a crucial role in model validation.

Table 3 and Table 4 present the retrieval results for wheel hub castings and engine cylinder block castings after integrating PDK. It is observed that although introducing process design features modestly enhances the retrieval accuracy of the CLCM method, the improvement remains limited. For other deep learning methods, incorporating process design features does not notably enhance the retrieval effectiveness for wheel hub castings, likely due to their distinctive shape characteristics that clearly differentiate them from other castings. Conversely, introducing process design features for engine cylinder blocks

Table 3: Retrieval results for wheel hub castings incorporating PDK

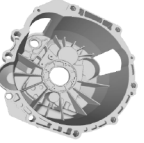
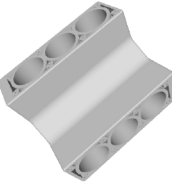
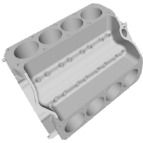
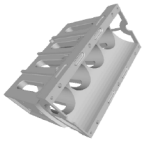
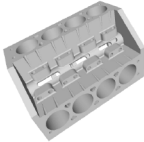
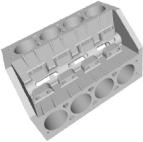
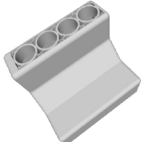
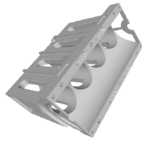
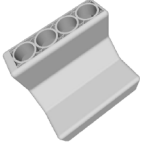
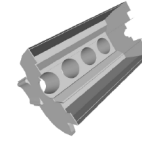
Query	Sorting	PDK	DINov2-PDK	CLIP-PDK	GLCM-PDK	VGG16-PDK	Resnet50-PDK
	A	 0.6625	 0.9773	 0.9890	 0.7479	 0.9276	 0.9551
	B	 0.6455	 0.9716	 0.9802	 0.7294	 0.9169	 0.9488
	C	 0.6271	 0.9646	 0.9758	 0.7130	 0.9072	 0.9323

Table 4: Retrieval results for engine cylinder block casting incorporating PDK

Query	Sorting	PDK	DINov2-PDK	CLIP-PDK	GLCM-PDK	VGG16-PDK	Resnet50-PDK
	A	 0.6708	 0.9708	 0.9898	 0.6097	 0.8483	 0.9483
	B	 0.6445	 0.9643	 0.9859	 0.5972	 0.8311	 0.9310
	C	 0.6298	 0.9501	 0.9729	 0.5771	 0.8276	 0.9181

leads to retrieved castings that closely match the target shapes, potentially because features like symmetry and aspect ratio not only reflect manufacturing requirements but also encode shape information. However, relying solely on process design features for retrieval shows that individual features alone may not be sufficient to find similar castings, underscoring the necessity of integrating both image and process design features.

To further validate the retrieval model’s accuracy, 10 labels were manually assigned to the dataset of unlabeled 3D models based on castings’ purpose and category. Using this method

for classification, the resulting model accuracy is depicted in Fig. 9. The CLIP model achieves the highest retrieval accuracy, scoring 91.73% and 97.82% before and after introducing PDK, respectively. The inclusion of PDK enhances accuracy across all models. These process design features embody domain experts’ knowledge and experience, reflecting critical casting attributes and properties. By integrating shape, appearance features, and process design characteristics, the model gains deeper insights into casting behavior, thereby improving overall accuracy.

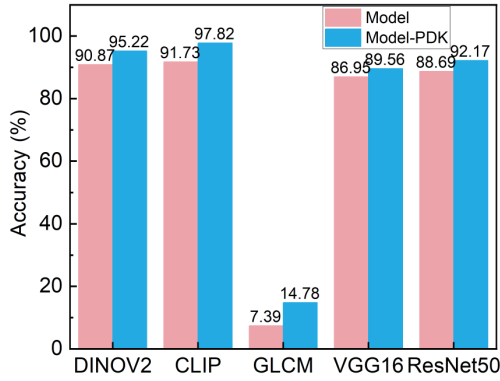


Fig. 9: Classification accuracy of each model

4 Discussion

Figure 10 presents the distribution of the process parameters of target (query) wheel hub model and process parameters of castings retrieved using the CLIP and CLIP-PDK models. Euclidean distances were used to calculate the similarity between process parameters, normalizing the distances to a range between 0 and 1 to represent similarity. Standardization was applied before calculating the Euclidean distance. The equations for standardization, Euclidean distance, and normalization are as follows:

$$z = \frac{x - \mu}{\sigma} \quad (8)$$

$$d_{\text{Euclidean}} = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (9)$$

$$N = 1 - \frac{d_{\text{Euclidean}} - \min(d_{\text{Euclidean}})}{\max(d_{\text{Euclidean}}) - \min(d_{\text{Euclidean}})} \quad (10)$$

where x represents the original vector value, μ is the mean, σ is the standard deviation, and z is the normalized value. x_i and y_i denote the i -th values of vectors x and y . N is the normalized value between 0 and 1, representing similarity. The calculation results are shown in Table 5. The CLIP-PDK-A wheel hub model shows the highest process parameter similarity to the query model at 41.68%, compared to 11.42% for the CLIP-A model without PDK, demonstrating a 30.26% improvement with PDK.

To further validate the effectiveness of the models in retrieving castings with reusable processes, the retrieved processes were applied to the target castings and performed numerical simulations using EasyCast software. The wheel

hub castings were made of ZL101A using low-pressure casting. Numerical simulation of casting can accurately model the filling and solidification of molten metal, predict defect locations, and optimize the process [51, 52]. Figure 11 shows the shrinkage cavity distribution with different process parameters. Compared to processes of CLIP_A model, using processes of CLIP-PDK_A model and CLIP-PDK_B model results in fewer shrinkage cavities. The main defects in wheel hub castings are concentrated at the junction of the spoke and rim, and the upper rim. The spoke-rim junction, being a thick-walled area, cools slowly and forms a hot spot. This hot spot cannot be effectively supplemented by liquid metal during solidification, making it prone to shrinkage. The upper rim is prone to shrinkage because it has a thicker cross-section than the main rim body, causing slower cooling. This prevents effective compensation during solidification, resulting in shrinkage cavity. Synergistic adjustment and optimization of parameters such as pressure, holding time, and pouring temperature can reduce shrinkage cavities. Introducing process design features, as opposed to direct design processes or using process parameters of castings with similar shapes alone, can significantly reduce process design and optimization time. Compared to other 3D casting model retrieval methods like the D2 and normal operators [53-55], which rely on manually designed shape and structural features, these approaches depend on subjective human interpretations of geometric shapes, potentially overlooking important subtle details. In contrast, deep learning models, automatically learn and extract multi-level features from 3D models, capturing complex geometric relationships

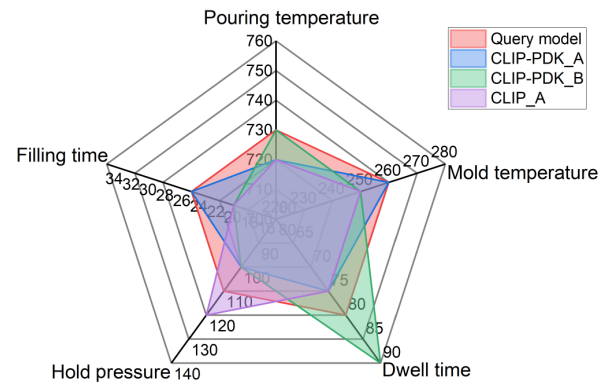


Fig. 10: Distribution of process parameters of target wheel hub model itself and process parameters for models with high similarity in CLIP and CLIP-PDK model retrieval results

Table 5: Similarity calculation results of processes for different castings

Casting model	Hold pressure (kPa)	Pouring temperature (°C)	Mold temperature (°C)	Dwell time (s)	Filling time (s)	Euclidean distance from process of query model	Similarity to process of query model
Query model	110	730	260	80	25	0	100%
CLIP_PDK_A	100	720	260	75	25	2.47	41.68%
CLIP_PDK_B	100	730	250	90	20	3.48	17.94%
CLIP_A	120	729	250	75	20	3.76	11.43%

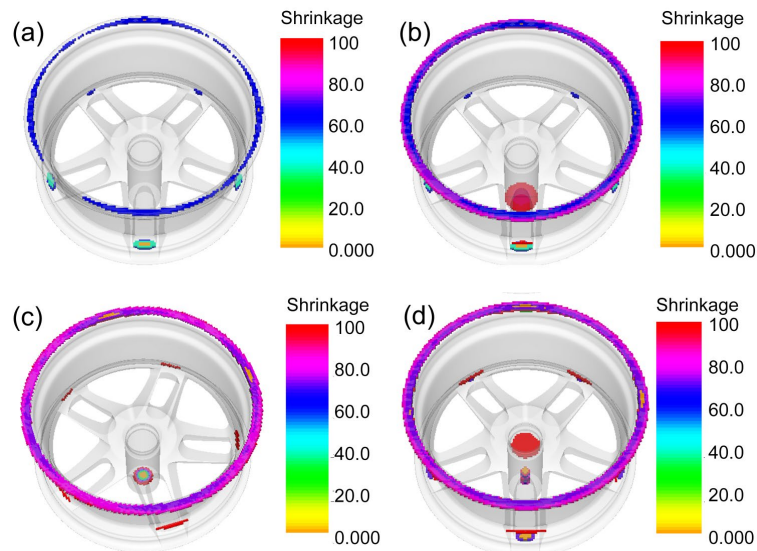


Fig. 11: Shrinkage cavity of low-pressure cast aluminum alloy wheels simulated by EasyCast under different processes: (a) Query model; (b) CLIP-PDK_A model; (c) CLIP-PDK_B model; (d) CLIP_A model

and high-dimensional characteristics while overcoming the limitations of manual feature selection. Both the D2 and normal operators require surface traversal of the 3D model to calculate distances, angles, and other geometric properties. This process can be computationally intensive, particularly for large or complex models, leading to slower retrieval speeds. However, traditional methods offer better interpretability compared to deep learning models.

5 Conclusion

Currently, relying solely on shape similarity in 3D model retrieval does not ensure the reusability of casting processes. In this study, a data-driven 3D model retrieval method was proposed, which integrates casting process design knowledge, enhancing process reuse by considering shape features and casting characteristics comprehensively. Using the CLIP model, shape features were extracted from three views and sectional view of castings and integrated with domain-specific features including module, main wall thickness, maximum wall thickness, minimum wall thickness, symmetry, length-to-height ratio, and width-to-height ratio. A casting database containing 230 actual castings was constructed to verify the method's effectiveness. Results show that the CLIP model, when integrated with PDK, achieves the highest accuracy of 97.82%, representing a 6.09% improvement over the methods relying solely on shape features, and a 30.25% increase in process similarity. Process reusability was validated using EasyCast casting simulation software, demonstrating that applying the process retrieved by CLIP model integrated with PDK results in minimal shrinkage cavity. This underscores the capability of the method to effectively recommend reusable casting processes. Additionally, materials are a key factor in casting process design. In future work, materials as a parameter for evaluating process similarity will be considered, which will further help expedite process reuse.

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Conflict of interest

Prof. Yu-hong Zhao is an EBM of *CHINA FOUNDRY*. She was not involved in the peer-review or handling of the manuscript. The authors have no other competing interests to disclose.

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- 722 |||||