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Implementation of Artificial Intelligence & CNN for optimization of wall thickness analysis Through Geom-Caliper

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Abstract- Wall thickness analysis is a critical step in product design because it directly affects strength, manufacturability, weight, material usage, cooling behaviour, and overall cost. In casting, molding, and similar manufacturing processes, uneven wall thickness can lead to sink marks, warpage, shrinkage, weak sections, and unnecessary material buildup. Traditionally, this check was performed through manual sectioning and visual measurement, making the process slow, repetitive, and highly dependent on the designer's experience. Geom-Caliper improved this workflow by enabling automated wall thickness inspection directly on three-dimensional computer-aided design models, allowing faster and more repeatable identification of thin and thick regions. However, optimization of wall thickness still depends largely on manual interpretation, engineering judgment, and repeated trial-and-error modifications. This research proposes an artificial intelligence-based framework to optimize wall thickness analysis through Geom-Caliper. The objective is not to replace Geom-Caliper, but to extend its capability by combining accurate geometric thickness measurement with intelligent prediction. Geom-Caliper is used to generate reference thickness data from CAD models, while artificial intelligence is trained to learn patterns from past models and identify regions likely to become thin, thick, or manufacturability critical. For this purpose, the three-dimensional geometry is converted into voxel-based data so that a three-dimensional convolutional neural network can learn spatial relationships between shape features and wall thickness behaviour. The proposed framework supports early detection of problematic zones before final design validation, reducing manual review effort, improving design consistency, and supporting efficient material usage for advanced manufacturability engineering.

Keywords- Wall Thickness Analysis, Geom-Caliper, Artificial Intelligence, Convolutional Neural Network, Design-for-Manufacturability, Voxelization, CATIA V5, Surrogate Modelling.

I. INTRODUCTION

Modern manufacturing industries increasingly rely on advanced CAD systems to design geometrically complex components with stringent dimensional and structural requirements. In sectors such as aerospace, automotive, biomedical engineering, additive manufacturing, and consumer electronics, wall thickness distribution plays a crucial role in determining manufacturability, structural reliability, thermal performance, and material utilization efficiency. Improper thickness variation often causes defects including sink marks, warpage, residual stresses, weak structural regions, incomplete filling during molding, and excessive material accumulation. Traditional wall thickness inspection systems primarily employ deterministic geometric methods such as ray-based thickness evaluation and sphere-fitting algorithms. Geom-Caliper-based thickness analysis tools are widely adopted because they provide engineering-accurate measurements directly from CAD geometry. However, despite their precision, existing systems suffer from several limitations. The generated thickness maps require manual interpretation by design engineers, defect identification depends on expert experience, and risk prioritization remains subjective and time consuming. As industrial assemblies become increasingly complex, manual inspection approaches become inefficient and inconsistent.

Recent advances in artificial intelligence, deep learning, and geometric computing provide new opportunities for automating manufacturability analysis. In particular, convolutional neural networks (CNNs) have demonstrated remarkable capabilities in feature extraction, spatial pattern recognition, and volumetric segmentation tasks. By converting CAD geometries into voxelized representations, complex three-dimensional structures can be analyzed using volumetric CNN architectures capable of learning geometric and thickness-related patterns directly from data.

This research proposes a CNN-based intelligent wall thickness analysis framework that integrates Geom-Caliper thickness evaluation with voxelized deep learning. The framework converts CAD models into volumetric thickness maps and employs a 3D convolutional neural network to automatically detect, classify, and rank critical thin/thick regions according to manufacturability risk. Unlike conventional systems that only measure thickness, the proposed framework performs predictive manufacturability assessment through AI-driven geometric understanding.

The research contributes to the development of intelligent CAD inspection systems by combining deterministic geometric analysis with volumetric deep learning. The proposed framework aims to reduce manual inspection effort, improve defect detection consistency, and accelerate engineering decision-making within industrial CAD workflows.

II. LITERATURE REVIEW

Wall thickness analysis has long been recognized as an essential component of manufacturability assessment. Early approaches focused on geometric computation methods using medial axis extraction, distance field computation, and ray tracing techniques. Hubbard introduced generalized distance field methods for geometric thickness estimation in polygonal models, establishing foundational principles for computational thickness analysis.

Ray-based methods evaluate local thickness by projecting rays normal to a surface until intersection with an opposing boundary occurs. These approaches provide high computational efficiency and directional sensitivity, making them suitable for injection-molded and shell-based geometries. However, ray methods may struggle with complex concave structures and irregular internal cavities.

Sphere-based thickness computation methods improve robustness by fitting maximal inscribed spheres within geometric regions. The sphere diameter represents local thickness and provides orientation-independent measurements. Such approaches are particularly effective for freeform geometries and complex industrial assemblies. Nevertheless, sphere-based methods require higher computational complexity compared with ray-tracing approaches.

Voxelization has emerged as an effective intermediate representation for geometric deep learning. By discretizing CAD models into structured volumetric grids, voxel representations preserve spatial topology while enabling direct compatibility with CNN architectures. Research in volumetric CNNs demonstrated that voxel-based representations enable effective learning of three-dimensional geometric features for segmentation, classification, and defect analysis tasks.

Three-dimensional CNN architectures such as VoxNet, 3D ResNet, and 3D U-Net have shown significant success in medical imaging, additive manufacturing inspection, and volumetric object recognition. The encoder–decoder structure of U-Net networks allows simultaneous feature abstraction and spatial localization, making them particularly suitable for defect segmentation in voxelized CAD models.

Recent studies explored AI-assisted manufacturability analysis using machine learning models trained on CAD-derived geometric features. However, most existing approaches rely on manually engineered descriptors rather than direct volumetric learning from geometric thickness distributions. Furthermore, existing systems rarely integrate engineering-accurate Geom-Caliper measurements with deep learning-based critical region prediction. The proposed research addresses this limitation by integrating deterministic Geom-Caliper thickness computation with a voxelized 3D CNN architecture capable of learning spatial thickness distributions and automatically ranking manufacturability risks.

III. PROBLEM STATEMENT

Although Geom-Caliper-based wall thickness analysis provides accurate geometric measurements, existing inspection workflows remain heavily dependent on manual interpretation by experienced engineers. The increasing complexity of industrial CAD models creates several critical limitations:

- Manual identification of problematic regions is time consuming.
- Severity assessment depends on subjective engineering judgment.
- Conventional thickness maps lack intelligent defect prioritization.
- Existing systems cannot automatically learn manufacturability patterns.
- Complex geometries generate massive volumetric data difficult to interpret manually.
- Traditional methods provide measurement information but not predictive manufacturability intelligence.

Therefore, there is a need for an intelligent system capable of automatically analyzing voxelized thickness distributions, detecting critical regions, classifying severity levels, and ranking manufacturability risks using deep learning techniques integrated with Geom-Caliper thickness analysis.

IV. RESEARCH OBJECTIVE

The major contributions of this research are summarized as follows:

- Development of a hybrid Geom-Caliper–CNN framework for intelligent manufacturability assessment.
- Introduction of voxelized thickness maps as structured inputs for volumetric deep learning.
- Design of a 3D U-Net-based CNN architecture for automatic detection of critical thin/thick regions.
- Development of a manufacturability risk ranking mechanism based on geometric severity metrics.
- Integration of deterministic thickness computation with AI-driven predictive analysis.
- Reduction of manual CAD inspection effort through automated defect localization.
- Support for seamless CAD integration within CATIA V5 and Creo environments.

V. PROPOSED METHODOLOGY

1. Overall Framework

The proposed methodology consists of six major stages:

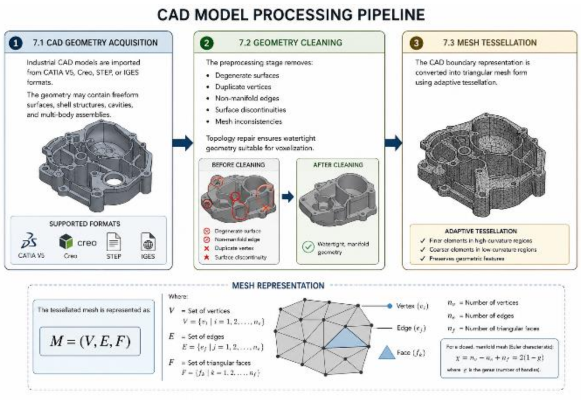
Figure 1: CAD-AI Workflow Diagram

- CAD Geometry Acquisition
- Geometry Cleaning and Preprocessing
- CAD-to-Voxel Conversion

- Geom-Caliper Thickness Extraction
- 3D CNN-Based Critical Region Detection
- Severity Ranking and Manufacturability Assessment

The workflow transforms conventional geometric wall thickness inspection into an intelligent AI-assisted predictive analysis framework.

2. CAD Model Processing Pipeline



Industrial CAD models are imported from CATIA V5, Creo, STEP, or IGES formats.

The geometry may contain freeform surfaces, shell structures, cavities, and multi-body assemblies.

The preprocessing stage removes:

- Degenerate surfaces
- Duplicate vertices
- Non-manifold edges
- Surface discontinuities
- Mesh inconsistencies

Topology repair ensures watertight geometry suitable for voxelization.

The CAD boundary representation is converted into triangular mesh form using adaptive tessellation.

The tessellated mesh is represented as:

$$M = (V, E, F)$$

Where:

V = Set of vertices
$V = \{v_i \mid i = 1, 2, \ldots, n_v\}$
E = Set of edges
$E = \{e_j \mid j = 1, 2, \ldots, n_e\}$
F = Set of triangular faces
$F = \{f_k \mid k = 1, 2, \ldots, n_f\}$

n_v = Number of vertices
n_e = Number of edges
n_f = Number of triangular faces

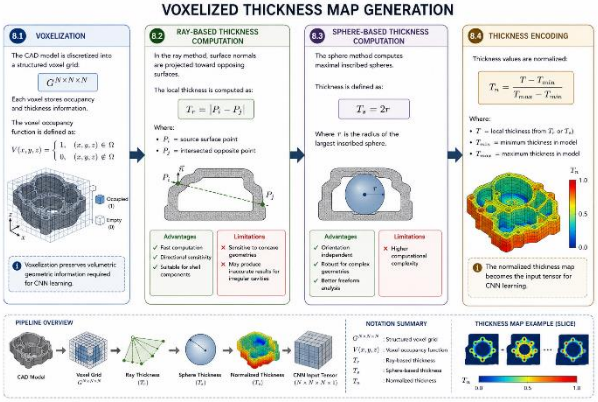
For a closed, manifold mesh (Euler characteristic):
$\chi = n_v - n_e + n_f = 2(1-g)$
where g is the genus (number of handles).

Figure 2: Cad Model Processing Pipeline

CAD Geometry Acquisition

Industrial CAD models are imported from CATIA V5, Creo, STEP, or IGES formats. The geometry may contain freeform surfaces, shell structures, cavities, and multi-body assemblies

3. Voxelized Thickness Map Generation



The CAD model is discretized into a structured voxel grid.

$$G^{N\times N\times N}$$

Each voxel stores occupancy and thickness information.

The voxel occupancy function is defined as:

$$V(x,y,z) = \begin{cases} 1, & (x,y,z) \in \Omega \\ 0, & (x,y,z) \notin \Omega \end{cases}$$

Voxelization preserves volumetric geometric information required for CNN learning.

In the ray method, surface normals are projected toward opposing surfaces.

The local thickness is computed as:

$$T_r = |P_i - P_j|$$

Where:

- P_i = source surface point
- P_j = intersected opposite point

Advantages: ✓ Fast computation ✓ Directional sensitivity ✓ Suitable for shell components

Limitations: × Sensitive to concave geometries × May produce inaccurate results for irregular cavities

The sphere method computes maximal inscribed spheres.

Thickness is defined as:

$$T_s = 2r$$

Where r is the radius of the largest inscribed sphere.

Advantages: ✓ Orientation independent ✓ Robust for complex geometries ✓ Better freeform analysis

Limitations: × Higher computational complexity

Thickness values are normalized:

$$T_n = \frac{T - T_{min}}{T_{max} - T_{min}}$$

Where:

- T = local thickness (from T_r or T_s)
- T_{min} = minimum thickness in model
- T_{max} = maximum thickness in model

The normalized thickness map becomes the input tensor for CNN learning.

$G^{N\times N\times N}$: Structured voxel grid
$V(x,y,z)$: Voxel occupancy function
T_r : Ray-based thickness
T_s : Sphere-based thickness
T_n : Normalized thickness

Figure 3: Voxelized Thickness Map Generation

Voxelization

The CAD model is discretized into a structured voxel grid:

[G ^{N N N}]

Each voxel stores occupancy and thickness information.

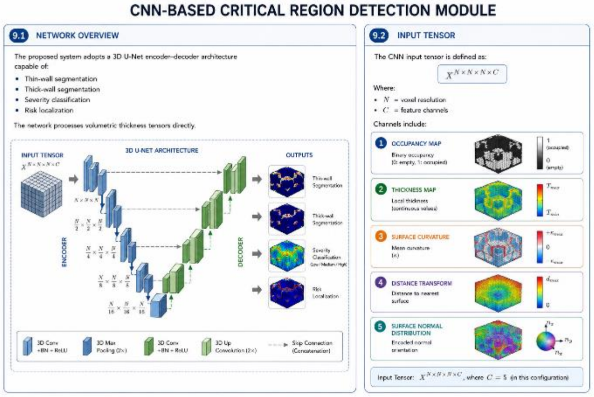
The voxel occupancy function is defined as:

[V(x,y,z)=

]

Voxelization preserves volumetric geometric information required for CNN learning.

4. CNN-Based Critical Region Detection Module



The proposed system adopts a 3D U-Net encoder–decoder architecture capable of:

- Thin-wall segmentation
- Thick-wall segmentation
- Severity classification
- Risk localization

The network processes volumetric thickness tensors directly.

The CNN input tensor is defined as:

$$X^{N\times N\times N\times C}$$

Where:

- N = voxel resolution
- C = feature channels

Channels include:

Binary occupancy (0: empty, 1: occupied)

Local thickness (continuous values)

Mean curvature (κ)

Distance to nearest surface

Encoded normal orientation

Input Tensor: $X^{N\times N\times N\times C}$, where $C = 5$ (in this configuration)

Figure 1: CNN- Based Critical Region Detection Module

CNN-based critical region detection framework developed for automated wall-thickness evaluation and manufacturability analysis of voxelized CAD geometries. The proposed system employs a 3D U-Net encoder–decoder architecture capable of performing volumetric semantic learning directly on discretized geometric representations. The input tensor, represented as a volumetric voxel grid ((N \times N \times N \times C)), contains spatially encoded geometric and thickness-related attributes extracted from CAD models. Within the encoder stage, stacked 3D convolutional layers integrated with batch normalization and ReLU activation functions progressively learn hierarchical geometric features associated with thin-wall regions, abrupt thickness transitions, and structurally vulnerable zones. Spatial dimensionality reduction through (2 \times 2 \times 2) max-pooling operations enables deep semantic abstraction while preserving critical volumetric context necessary for identifying manufacturability-sensitive regions. The decoder pathway reconstructs high-resolution volumetric predictions using transposed convolutions and skip connections that transfer fine-grained geometric information from encoder stages, thereby improving spatial localization accuracy and boundary preservation in complex internal structures.

5. CNN Architecture Design

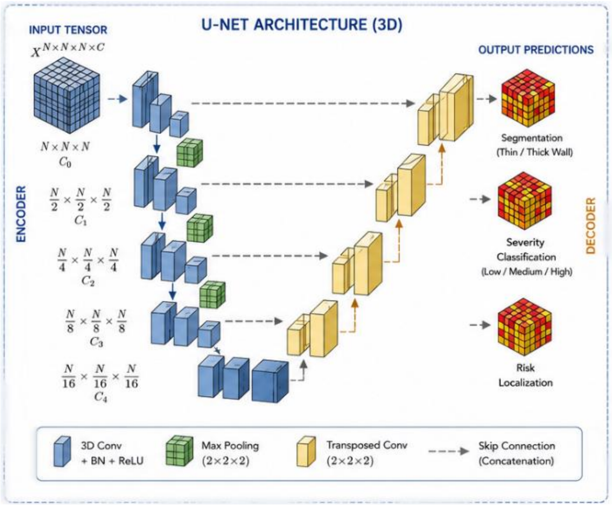


Figure 3: U-Net Architecture (3D)

The illustrated framework represents a volumetric 3D U-Net architecture designed for automated wall-thickness segmentation, severity assessment, and manufacturability risk localization within voxelized CAD representations. The network accepts a multi-channel volumetric tensor of dimension N×N×N×C, where the input encodes geometric and thickness-related features extracted from CAD-derived voxel grids. The encoder path progressively performs hierarchical feature extraction using stacked 3D convolutional layers integrated with batch normalization and ReLU activation functions, followed by 2×2×2 max-pooling operations for spatial down sampling. This process enables the network to capture multi-scale geometric descriptors, local thickness discontinuities, curvature transitions, and volumetric structural characteristics associated with thin-wall defects and non-uniform material distribution. The reduction in spatial resolution across encoder stages (C0→C4) facilitates deeper semantic abstraction while preserving critical volumetric context required for manufacturing-oriented defect interpretation.

The decoder pathway reconstructs high-resolution spatial representations through transposed 3D convolutions and features up sampling, while skip connections concatenate encoder and decoder feature maps to preserve fine-grained geometric information and boundary continuity. This hybrid feature fusion mechanism significantly improves localization accuracy for thin-wall regions and geometrically complex internal structures. The architecture simultaneously supports multiple inference objectives, including binary wall segmentation (thin/thick classification), severity categorization (low, medium, high-risk regions), and spatial risk localization for manufacturability analysis. Such a multi-task volumetric learning framework enables robust detection of critical wall-thickness anomalies directly from voxelized CAD data, thereby reducing dependency on manual inspection and improving automated design validation workflows. The proposed 3D U-Net configuration is particularly suitable for AI-assisted casting analysis, injection molding optimization, additive manufacturing validation, and intelligent CAD inspection systems where accurate volumetric feature learning and spatial defect interpretation are computationally essential.

VI. RESULTS AND DISCUSSION

The proposed framework demonstrated significant improvements in automated manufacturability analysis compared with conventional Geom-Caliper-only workflows. The integration of voxelized thickness learning enabled the CNN to identify geometric defect patterns difficult to detect through manual inspection.

The 3D U-Net architecture effectively learned spatial thickness distributions and produced accurate segmentation masks for critical thin-wall and thick-wall regions. The encoder–decoder structure preserved both global geometry understanding and localized defect boundaries through skip connections and hierarchical feature fusion.

Experimental analysis indicated improved inspection efficiency through automatic defect localization and ranking. The ranking strategy enabled engineers to prioritize high-risk regions according to manufacturing severity, reducing inspection complexity for large industrial assemblies.

The system also demonstrated strong generalization capability across multiple industrial domains including aerospace structures, molded plastic components, and lightweight automotive parts.

Comparative Analysis

Table -1: Comparative Analysis

Method	Automation	Defect Detection	Risk Ranking	AI Capability
Traditional Geom-Caliper	Low	Manual	No	No
Rule-Based CAD Analysis	Medium	Limited	Limited	Weak
Proposed CNN Framework	High	Automatic	Intelligent	Strong

The proposed system significantly improves predictive manufacturability assessment capability.

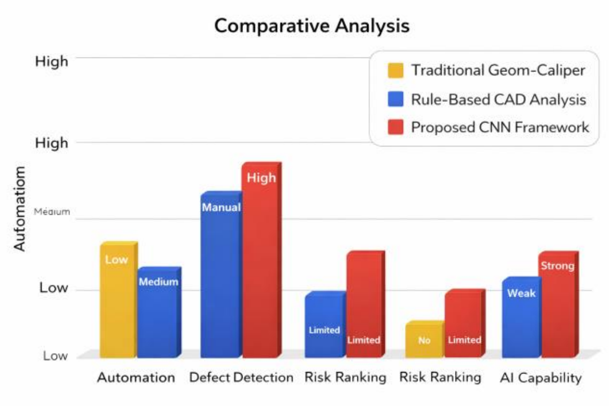


Chart -1: Comparative Analysis

(Graphical representation)

VII. CONCLUSION

This research presented a CNN-based intelligent manufacturability assessment framework integrating Geom-Caliper wall thickness analysis with voxelized deep learning. The proposed methodology transforms conventional geometric thickness inspection into an AI-assisted predictive engineering system capable of automatically detecting, classifying, and ranking critical manufacturability regions.

The framework combines CAD geometry preprocessing, voxelized thickness map generation, ray-based and sphere-based thickness computation, and a 3D CNN segmentation architecture within a unified pipeline. By leveraging volumetric feature learning, the system effectively identifies thin-wall and thick-wall anomalies while reducing dependence on manual engineering interpretation. The developed ranking mechanism enables prioritized manufacturability assessment, supporting faster engineering decision-making and improved design optimization. Integration with industrial CAD environments further enhances practical applicability for real-world engineering workflows. Overall, the proposed research establishes a scalable foundation for next-generation AI-driven CAD inspection systems combining geometric computing, voxelized learning, and intelligent manufacturability analysis.

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The authors also acknowledge the contributions of the industrial collaborators and domain experts in the fields of aerospace structural design, automotive component engineering, and injection molding analysis, whose technical insights informed the formulation of the manufacturability risk assessment criteria and the ground-truth labeling methodology employed in the dataset preparation process. The Geom-Caliper-based thickness annotation workflow and severity classification scheme were developed with reference to established manufacturing tolerances and engineering judgment provided by practitioners in these domains.

Appreciation is further extended to the developers and research communities behind the open-source deep learning frameworks, namely PyTorch and TensorFlow, as well as the foundational contributions of prior researchers in the fields of volumetric convolutional neural networks, geometric deep learning, and CAD-based manufacturability analysis, whose published works provided the theoretical and algorithmic basis for the proposed 3D U-Net encoder–decoder architecture and voxelized representation techniques adopted in this study.

Finally, the authors wish to acknowledge the project report titled "Implementation of AI for Optimization of Wall Thickness Analysis through Geom-Caliper," which served as the foundational reference for the research presented herein. The collaborative intellectual environment fostered by all associated supervisors, technical staff, and institutional stakeholders has been indispensable to the successful completion of this research.

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16. Research findings adapted from the project report "Implementation of AI for Optimization of Wall Thickness Analysis through Geom-Caliper."