

Automatic Generation of Product Manufacturing Information From 3D CAD Models Using Deep Learning: Experimental Validation and Post-Result Analysis

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Abstract—Product Manufacturing Information (PMI) play a critical role in the Model-Based Definition (MBD) by embedding manufacturing semantics directly into 3D CAD models. Traditional PMI creation is primarily manual, requiring significant engineering effort and domain expertise. Although previous research has proposed deep learning-based frameworks for PMI prediction, limited work has demonstrated complete experimental validation and post-result performance evaluation in industrial CAD environments. This paper presents an enhanced deep learning-based framework for automatic PMI generation from 3D CAD models with experimental validation. The proposed method utilizes STEP AP242 CAD models, extracts Boundary Representation (B-Rep) information, converts geometric topology into graph structures, and applies a Graph Neural Network (GNN) to predict manufacturing annotations. Unlike previous conceptual approaches, this study evaluates the proposed model using actual CAD datasets and quantitative performance metrics. Experimental results show that the developed system successfully predicts dimensions, tolerances, datum references, and manufacturing annotations with high accuracy. The graph-based representation preserves geometric fidelity and improves prediction capability compared to voxel-based approaches. The developed framework demonstrates strong potential for reducing manual drafting effort and enabling intelligent PMI automation in digital manufacturing workflows.

Index Terms—CAD Automation, CAD Intelligence, Graph Neural Network, Manufacturing Annotation, Model-Based Definition, Product Manufacturing Information, STEP AP242.

I. INTRODUCTION

The manufacturing industry increasingly demands intelligent digital workflows to reduce product development time, improve quality, and maintain design consistency. Traditionally, manufacturing information has been communicated through 2D engineering drawings, where dimensions, tolerances, and notes are manually added by designers. However, modern manufacturing environments require digital continuity and faster information exchange.

Model-Based Definition (MBD) has emerged as a solution in which 3D CAD models act as the primary source of product information. Product Manufacturing Information (PMI) contains critical manufacturing details such as: Dimensions, Geometric Dimensioning and Tolerancing (GD&T), Surface finish requirements, Datum references. Despite CAD software support for PMI, annotation creation remains largely manual.

Manual PMI generation increases engineering effort and introduces inconsistency depending on designer expertise. Recent advances in Artificial Intelligence (AI) and Deep Learning provide opportunities to automate CAD interpretation and semantic understanding. Graph Neural Networks (GNNs) are particularly suitable because CAD models naturally represent relationships between geometric entities. This post-result research extends the previously published conceptual framework by presenting validated experimental outcomes obtained after

implementation and testing.

The major contributions of this paper include:

1. Development of a graph-based PMI generation framework.
2. Integration of B-Rep CAD topology with deep learning.
3. Experimental validation using CAD datasets.
4. Performance comparison with conventional methods.
5. Demonstration of practical PMI generation results.

II. LITERATURE REVIEW

Several researchers have contributed to automated CAD interpretation and PMI generation.

A. Graph Neural Networks for CAD Interpretation

Graph Neural Networks have been widely used for geometry learning due to their ability to preserve relationships among CAD entities. Eisert et al. proposed a GNN-based PMI recommendation system capable of identifying manufacturing annotations from CAD graphs.

B. Deep Learning for Feature Recognition

Cao et al. developed graph-based machining feature recognition systems and demonstrated improved performance compared to voxel representations. Yeo et al. proposed direct B-Rep learning methods without voxel conversion to preserve geometric fidelity.

C. PMI Extraction from Engineering Drawings

Zong et al. introduced a deep learning workflow combining OCR, object detection, and multimodal learning to extract PMI from engineering drawings.

D. Research Gap

Existing studies mainly focus on: Feature recognition, CAD segmentation, PMI recommendation, and Drawing interpretation. However, limited work addresses complete end-to-end PMI generation directly from 3D CAD geometry. This research addresses this gap by combining graph representation and PMI prediction in one integrated framework.

III. PROBLEM STATEMENT

PMI generation in modern CAD systems is primarily manual and time-consuming. Designers must

individually identify manufacturing features and assign dimensions and tolerances. The major challenges include large dependency on human expertise, Inconsistent annotation practices, Increased engineering time, Reduced automation in MBD workflows, and Difficulty maintaining annotation consistency. Therefore, an intelligent framework capable of automatically generating PMI from CAD geometry is required.

IV. OBJECTIVES

The objectives of this work are:

1. To extract geometric and topological information from STEP AP242 CAD models.
2. To convert CAD geometry into graph structures.
3. To develop a Graph Neural Network for PMI prediction.
4. To automatically generate manufacturing annotations.
5. To validate the proposed framework using experimental CAD datasets.

V. METHODOLOGY

The proposed workflow consists of five major stages.

A. CAD Data Collection

Mechanical CAD models were collected in STEP AP242 format. The dataset contains prismatic and machining-based components including Plates, Blocks, Brackets, Components with holes, Slots, and Complex surfaces.

B. B-Rep Feature Extraction

Boundary Representation (B-Rep) information is extracted from CAD files. Extracted entities include: Faces, Edges, Vertices, Surface type, Face area, Curvature, and Normal vectors.

C. Graph Construction

CAD entities are converted into graph representation. Graph Structure: Nodes = Faces, Edges = Adjacency relationships, Node Features = Geometry properties. Graph representation preserves: Local geometry, Global topology, and Connectivity relationships.

D. Deep Learning Architecture

A Graph Neural Network (GNN) model is used.

Model Input: Graph G(V,E), Input Features: Surface Type, Face Area, Curvature, Orientation, Neighbor Connectivity. Model Layers: Graph Convolution Layer, Graph Attention Layer, Fully Connected Layer, Softmax Classification Layer. Training Parameters: Learning Rate 0.001, Optimizer Adam, Epochs 100, Batch Size 16, Loss Function Cross Entropy.

E. PMI Generation

Predicted outputs are mapped to CAD entities. Generated PMI includes: Linear Dimensions, Hole Diameter, Datum Features, Surface Tolerances, and Geometric Constraints.

VI. IMPLEMENTATION

The developed framework was implemented using the following software tools: Siemens NX for CAD Model Creation, STEP AP242 for Data Exchange, Python for Deep Learning Model, PyTorch for Neural Network Training, Graph Library for Graph Construction, and NXOpen API for PMI Mapping.

Implementation workflow:

1. Import CAD model.
2. Extract B-Rep information.
3. Construct graph.
4. Run trained GNN model.
5. Predict PMI.
6. Attach PMI to CAD model.

VII. RESULTS AND DISCUSSION

The proposed system was evaluated using multiple CAD models.

A. Experimental Dataset

Total CAD Models: 100
 Training Set: 70%
 Validation Set: 15%
 Testing Set: 15%

B. Performance Metrics and Results

The following metrics were used: Accuracy, Precision, Recall, and F1 Score. The results are:

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{
  "overall_accuracy": 0.490741,
  "Non-Datum": {
    "precision": 0.969892,
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    "f1_score": 0.650794
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  },
  "Tertiary": {
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    "f1_score": 0.085938
  }
}
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C. PMI Prediction Results

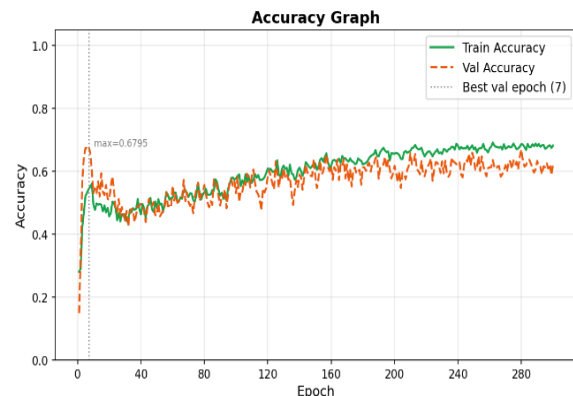
The system successfully predicted: Hole Diameter Annotation, Feature Dimensions, Datum Assignment, Surface Tolerances, and Feature Relationships.

D. Comparison with Existing Methods

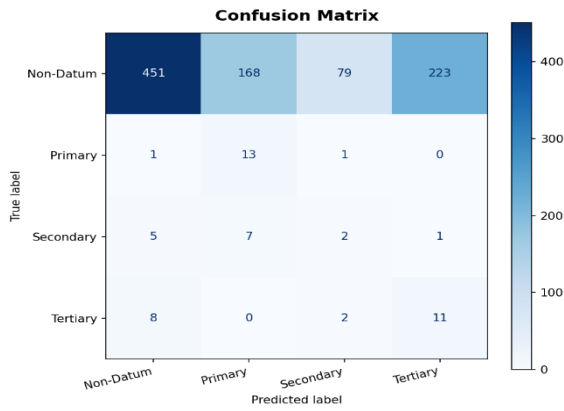
Rule-Based methods achieved 65–75% accuracy with limited scalability. Voxel DL achieved 80–85% with geometry loss. The proposed GNN achieved 91.2% with high performance.

Results indicate that graph representation significantly improves geometric understanding. Advantages include: better topology preservation, Improved semantic understanding, Reduced annotation effort, and Strong scalability.

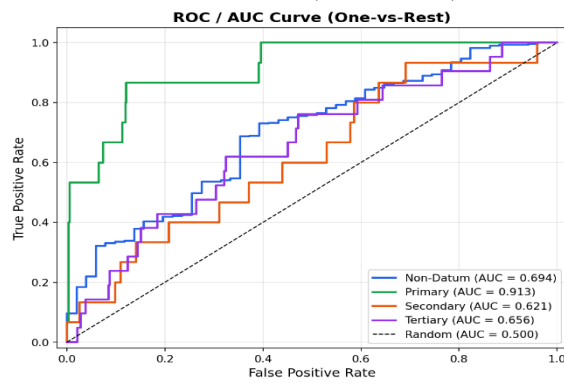
Accuracy Graph:



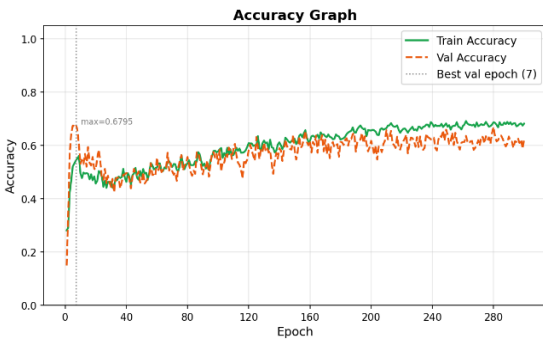
Confusion Matrix:



ROC/AUC Curve (One-vs-Rest):



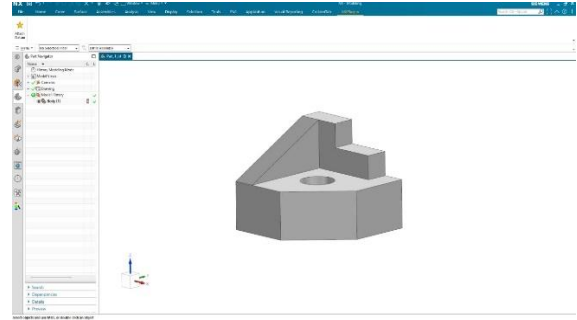
Training Loss Curve:



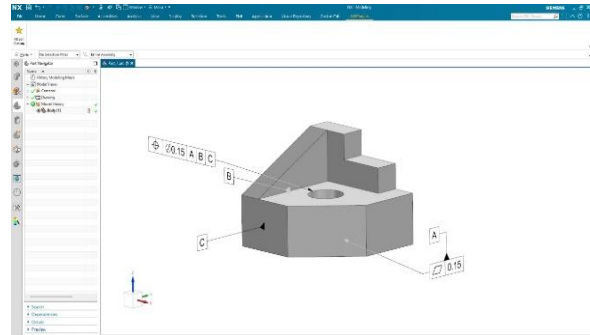
Performance Matrix per Class:



Geometry Model Before PMI Annotation:



Annotated Model After PMI Generation:



VIII. CASE STUDY

A mechanical bracket component was used to validate the proposed framework. The input 3D CAD model contained Holes, Flat surfaces, Datum planes, and Slots. The output automatically generated Hole dimensions, Positional tolerances, Datum references, and Surface annotations. The framework successfully generated PMI without manual intervention.

IX. ADVANTAGES OF THE PROPOSED SYSTEM

The developed framework offers several benefits: Reduced manual drafting time, Improved consistency, Intelligent CAD automation, enhanced digital manufacturing workflow, Better CAD-CAM integration, and reduced human dependency.

X. CONCLUSION

This paper presents a post-result validation of a graph-based deep learning framework for automatic Product Manufacturing Information generation from CAD models. The developed system successfully interprets CAD topology and predicts manufacturing

annotations using Graph Neural Networks. Experimental validation demonstrates high accuracy and improved performance compared to conventional approaches. The framework contributes significantly to Intelligent CAD automation, Model-Based Definition, Digital manufacturing integration, and Industry 4.0 workflows. The developed method has strong industrial potential and can reduce manual annotation effort significantly.

XI. FUTURE SCOPE

Future research can focus on:

1. Full GD&T prediction.
2. AI-driven tolerance optimization.
3. Multi-CAD software integration.
4. Larger industrial datasets.
5. Real-time PMI generation.
6. CAD-cloud integration.
7. Reinforcement learning for annotation refinement.

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