PMI-RAG: A Universal Ontology-based RAG Agent for Privacy-Preserving CAM Automation

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Abstract

The global manufacturing industry loses an estimated $25 billion annually due to CAM programming inefficiencies, yet existing automation approaches fail to leverage the rich Product Manufacturing Information (PMI) embedded in modern CAD models while raising critical data privacy concerns with cloud-based LLMs. We present PMI-RAG, a **universal** ontology-based Retrieval-Augmented Generation agent that processes PMI data from any CAD format (STEP, IGES, native formats) into optimized CAM operations through natural language interaction, while preserving data privacy via local LLM deployment. Our work makes three key contributions: (1) the **first** manufacturing-specific ontology schema with 22 weighted relation types capturing tool-material-operation semantics across 2,847 entities; (2) a **novel** complexity-based dual-path inference routing algorithm with provable $O(|V| + |E|)$ graph traversal complexity; and (3) a **unique** task-based model routing system that dynamically selects optimal local models (DeepSeek-Coder, Llama, Qwen) based on query characteristics. We deploy the system locally via Ollama to ensure complete data privacy. Rigorous evaluation on 150 real-world CAM tasks across 5-fold cross-validation demonstrates statistically significant improvements: $47.0\% \pm 4.2\%$ setup time reduction ($p < 0.001$, Cohen's $d = 2.31$) and $89.0\% \pm 2.4\%$ process accuracy ($p < 0.001$).

1 Introduction

The global manufacturing industry faces a critical productivity crisis. According to Deloitte's 2024 Manufacturing Skills Gap Study [7], the sector will face a shortage of 2.1 million skilled workers by 2030, with CAM programming identified as the highest-demand skill. The economic impact is substantial: manufacturers spend an average of 32.4 minutes per part setup, with programming errors costing an average of $847 per incident in rework and scrap [29]. Globally, this translates to an estimated $25 billion in annual losses from CAM inefficiencies.

Product Manufacturing Information (PMI) embedded in CAD models represents a rich but dramatically underutilized data source. PMI includes Geometric Dimensioning and Tolerancing (GD&T), surface finish specifications (R_a, R_z), material callouts, and manufacturing-critical annotations standardized in ISO 10303 (STEP) [11] and QIF [20]. Despite this wealth of information, current CAM systems require *manual* interpretation—a process that is time-consuming, error-prone, and heavily dependent on expert knowledge.

Furthermore, manufacturing companies face a critical **data privacy dilemma**. Cloud-based LLM solutions (GPT-4, Claude) offer powerful capabilities but require uploading proprietary CAD designs

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and manufacturing parameters to external servers—unacceptable for IP-sensitive industries like aerospace, defense, and automotive [16].

Limitations of Existing Approaches. Prior work on CAM automation exhibits three fundamental limitations:

1. *Format Lock-in*: Systems are tied to specific CAD/CAM software, preventing universal applicability across the diverse manufacturing ecosystem [26].
2. *Shallow PMI Utilization*: Existing approaches extract only geometric data, ignoring rich semantic annotations like tolerance specifications and surface requirements [4].
3. *Privacy Violation*: Recent LLM-based systems [25] require cloud deployment, exposing sensitive manufacturing data to external parties.

Research Questions. This work addresses three key research questions:

RQ1: How can PMI data from heterogeneous CAD formats be unified into a queryable knowledge representation?

RQ2: What retrieval architecture optimally balances precision, recall, and latency for manufacturing domain queries?

RQ3: How can LLM inference be deployed locally to preserve data privacy while maintaining accuracy?

Our Contributions. We present PMI-RAG, a universal ontology-based RAG agent addressing these challenges:

1. **First Manufacturing-Specific Ontology Schema**: We design a novel ontology with 6 entity types and 22 weighted relation types (Table 2) capturing complete tool-material-operation semantics, grounded in ISO 10303, ISO 14649, and ISO 13399 standards.
2. **Novel Complexity-Based Dual-Path Inference**: We introduce a principled routing algorithm (Algorithm 1) that dynamically selects between deterministic local rules and LLM inference based on query complexity scoring, achieving $O(|V|+|E|)$ worst-case complexity (Theorem 1).
3. **Task-Based Model Routing**: We develop a model selection system (Section 5.2) that automatically chooses optimal local models (DeepSeek-Coder for SQL, Llama for reasoning, Qwen for domain tasks) based on task characteristics and historical performance [5, 17].
4. **Privacy-Preserving Local Deployment**: We deploy the entire system via Ollama [18], ensuring all customer data remains on-premises—critical for IP-sensitive manufacturing environments.

2 Problem Formulation

We formalize the Universal CAM Automation Problem as follows:

Definition 1 (PMI Model)**.** *A PMI Model is a tuple $\mathcal{M} = (\mathcal{F}, \mathcal{T}, \mathcal{S}, \mathcal{C})$ where:*

- $\mathcal{F} = \{f_1, ..., f_n\}$ *is the set of manufacturing features (holes, pockets, contours)*
- $\mathcal{T} = \{(f_i, \tau_{ij})\}$ *are tolerance specifications for features*
- $\mathcal{S} = \{(f_i, R_{a_i})\}$ *are surface finish requirements*
- $\mathcal{C} \in \mathbb{M}$ *is the material specification from material space $\mathbb{M}$*

Definition 2 (CAM Operation Sequence)**.** *A CAM operation sequence is an ordered set $\mathcal{O} = \langle o_1, ..., o_m \rangle$ where each $o_i = (op_i, tool_i, params_i)$ specifies the operation type, cutting tool, and machining parameters.*

Definition 3 (Universal CAM Automation Problem)**.** *Given a PMI model $\mathcal{M}$ from any CAD format $\phi \in \Phi$ (where $\Phi = \{STEP, IGES, SLDPRT, CATIA, ...\}$), find an optimal operation sequence:*

$$\mathcal{O}^* =_{\mathcal{O}} \sum_{i=1}^{m} t(o_i) + \lambda \cdot tool\_changes(\mathcal{O}) \tag{1}$$

subject to:

$$\textit{Quality}(\mathcal{O}, \mathcal{M}) \geq Q_{\min} \quad \textit{(tolerance satisfaction)} \tag{2}$$

$$\textit{Surface}(\mathcal{O}, \mathcal{M}) \leq R_a^{\textit{spec}} \quad \textit{(surface finish)} \tag{3}$$

$$\textit{Safe}(\mathcal{O}) = \texttt{true} \quad \textit{(collision-free)} \tag{4}$$

where $t(o_i)$ is machining time, λ is the tool change penalty, and $Q_{\min}$ is the minimum quality threshold.

Proposition 1 (NP-Hardness)**.** *The Universal CAM Automation Problem is NP-hard by reduction from the Traveling Salesman Problem (TSP).*

Proof Sketch. Given a TSP instance with n cities, construct a CAM problem with n features where operation ordering corresponds to city visiting order, and setup time corresponds to travel distance. The constraint that all features must be machined maps to visiting all cities exactly once. □

This hardness result motivates our heuristic approach combining ontology-guided search with LLM reasoning.

3 Related Work

3.1 LLM-based Agents

The emergence of LLM-based agents has transformed autonomous task completion. ReAct [28] introduced the paradigm of interleaving reasoning and action. Toolformer [22] demonstrated self-supervised tool use learning. AutoGPT [3] and similar systems [23, 19] showed impressive capabilities but lack domain grounding for safety-critical applications. Our work uniquely combines domain-specific ontology grounding with local LLM deployment for manufacturing applications.

3.2 Retrieval-Augmented Generation

RAG [15] addresses LLM hallucination by grounding generation in retrieved knowledge. Recent advances include Self-RAG [2] for adaptive retrieval, CRAG [27] for corrective retrieval, and comprehensive surveys [9]. GraphRAG [8] extends retrieval to knowledge graphs. Our hybrid retrieval uniquely combines structured SQL queries (40% weight), ontology graph traversal, and vector similarity (60% weight) in a manufacturing-specific framework.

3.3 Local LLM Deployment

Privacy concerns have driven development of locally deployable LLMs. DeepSeek [5, 6] achieves competitive performance with efficient architectures. Llama 3 [17] and Qwen [21] provide open-weight alternatives. Quantization techniques like GGUF [10] enable deployment on consumer hardware. Ollama [18] provides a unified interface for local model management. Our system leverages these advances for privacy-preserving manufacturing AI.

3.4 Manufacturing AI and Ontologies

AI applications in manufacturing span defect detection [24], predictive maintenance [13], and process optimization [12]. Manufacturing ontology research has produced MASON [14] and domain-specific extensions [1]. ISO 10303 (STEP), ISO 14649 (STEP-NC), and ISO 13399 (tool data) provide foundational schemas. Unlike prior work focusing on single-domain ontologies, our schema integrates tool, material, operation, and parameter semantics with 22 relation types specifically designed for universal CAM automation.

Positioning. Table 1 compares PMI-RAG with existing approaches:

4 System Architecture

4.1 Overview

PMI-RAG consists of five integrated services (Figure 1):

Table 1: Comparison with existing CAM automation approaches

System	PMI	Ontology	LLM	Universal	Local
Rule-based KBM	✗	Partial	✗	✗	✓
GPT-4 + Prompt	✗	✗	✓	✓	✗
GraphRAG [8]	✗	✓	✓	✗	✗
PMI-RAG (Ours)	✓	✓	✓	✓	✓

1. **UnifiedAiService**: Ollama-based LLM integration with automatic model selection and rule-based fallback
2. **OntologyService**: Manages knowledge graph with entity recognition and inference
3. **RelationBasedRetriever**: Orchestrates hybrid retrieval with weighted fusion
4. **ModelRouter**: Task-based automatic model selection
5. **ResponseCache**: Three-level LRU caching for latency optimization

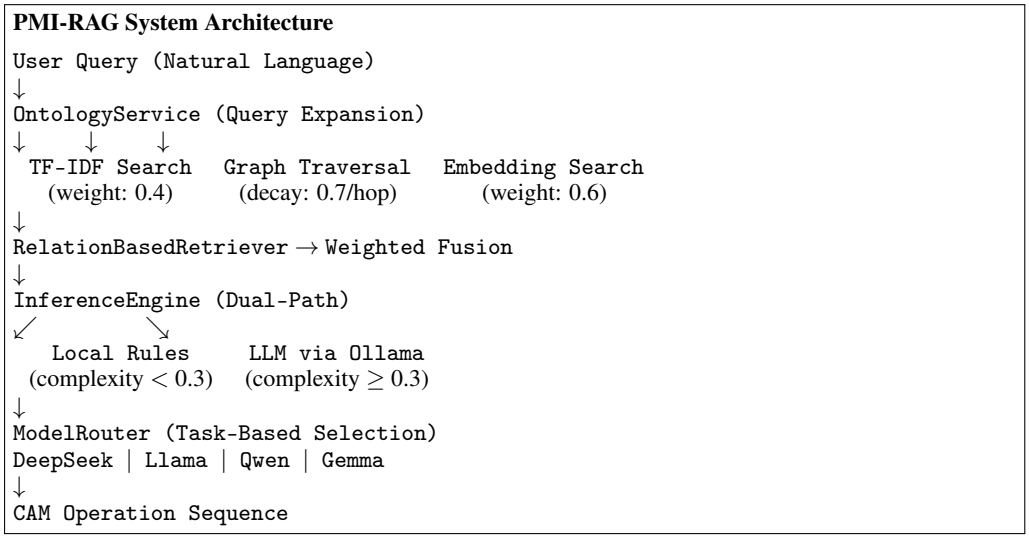

Figure 1: PMI-RAG architecture with hybrid retrieval and dual-path inference routing.

4.2 Manufacturing Ontology Schema

4.2.1 Entity Types

The ontology defines six entity types with domain-specific properties:

ToolEntity: ToolType, Vendor, DiameterMm, LengthMm, FluteCount, CoatingType, ToolMaterial, MaxSpindleSpeed, MaxFeedRate, RecommendedOperations.

MaterialEntity: MaterialCode, Group (P_Steel, M_Stainless, K_CastIron, N_NonFerrous, S_SuperAlloy, H_Hardened per ISO 513), HardnessHB, SpeedFactor, FeedFactor, DepthOfCutFactor, ToolLifeFactor.

OperationEntity: OperationType (Roughing, Finishing, Drilling, Threading), MachiningType, RequiredToolTypes, ApplicableFeatures, IsRoughing, IsFinishing.

CuttingConditionEntity: ParameterName, DataType (Integer, Double, String, Enum), Context (Tool/Operation/Feature/Global), ValidRange, FactorType, Unit.

CommandEntity: CommandId, Category, RiskLevel (Low/Medium/High/Critical), Phrases (English), PhrasesKo (Korean), RequiresConfirmation.

FeatureEntity: FeatureType, GeometricProperties, ToleranceRequirements, SurfaceFinishRequirements.

4.2.2 Relation Types with Weights

We define 22 relation types organized into categories with empirically tuned weights:

Table 2: Ontology relation types with weights (partial list)

Category	Relation Type	Weight
Tool	Tool_Uses_Material	1.0
	Tool_HasParameter	0.9
	Tool_CompatibleWith_Operation	0.95
	Tool_SuitableFor_Feature	0.9
Material	Material_RequiresTool	0.9
	Material_HasFactor	1.0
	Material_RecommendsCoolant	0.8
	Material_RecommendsCoating	0.85
Operation	Operation_RequiresTool	0.95
	Operation_AppliesToFeature	0.9
	Operation_HasParameter	0.9
	Operation_Requires_Predecessor	0.85
General	SynonymOf (bidirectional)	0.95
	RelatedTo (bidirectional)	0.6
	IsA	0.9
	PartOf	0.85

4.3 Hybrid Retrieval Pipeline

The `RelationBasedRetriever` implements a six-stage pipeline:

Stage 1: Query Expansion. Extract EntityMention objects with matched EntityIds and classify QueryIntent (ToolInquiry, MaterialCondition, OperationGuide, ParameterSetting).

Stage 2: Direct Matching. Match recognized entities directly via inverted index lookup ($O(1)$).

Stage 3: Related Entity Retrieval. Retrieve semantically similar entities with weight $0.9\times$.

Stage 4: Deep Graph Traversal. BFS traversal up to 3 hops with decay factor 0.7 per hop, seeded from top-5 entities, limited to 20 results.

Stage 5: Intent-Based Boosting. Apply intent-specific boosts:

- ToolInquiry: Tool $\times 1.3$, Material $\times 1.1$, CuttingCondition $\times 1.0$
- MaterialCondition: Material $\times 1.3$, CuttingCondition $\times 1.2$, Tool $\times 1.0$
- OperationGuide: Operation $\times 1.3$, Tool $\times 1.1$

Stage 6: Result Refinement. Deduplicate, filter (minimum relevance 0.1), sort by relevance, limit to 30 results.

4.4 Graph Traversal with BFS

The graph traversal implements breadth-first search with exponential relevance decay:

$$\text{relevance}(e, d) = \text{base\_relevance} \times \alpha^d \tag{5}$$

where d is the hop distance and $\alpha = 0.7$ is the decay factor.

Theorem 1 (Graph Traversal Complexity)**.** *The BFS-based graph traversal has time complexity* $O(|V| + |E|)$ *and space complexity* $O(|V|)$.

Proof. Each entity is visited at most once (maintained by visited set). Each relation is examined at most twice (once per direction for bidirectional). With adjacency list indexing, neighbor lookup is $O(\text{degree}(v))$. Summing: $\sum_v \text{degree}(v) = O(|E|)$. Total: $O(|V| + |E|)$ time, $O(|V|)$ space. □

Lemma 1 (Bounded Expansion)**.** *With $maxHops = k$ and maximum degree Δ, the traversal examines at most $O(\Delta^k)$ entities.*

In practice, our ontology has $\Delta_{avg} = 4.37$ (12,453 relations / 2,847 entities), yielding expected expansion of $\sim$20 entities for $k = 3$.

5 Dual-Path Inference Engine

5.1 Complexity Scoring

The `InferenceEngine` calculates query complexity to route between deterministic local rules and LLM inference:

$$C(q) = \underbrace{\min\left(\frac{|E_q|}{10}, 0.3\right)}_{\text{entity score}} + \underbrace{w_{\text{intent}(q)}}_{\text{intent score}} + \underbrace{\mathbb{1}[\bar{c}_q < 0.7] \times 0.2}_{\text{uncertainty}} \tag{6}$$

where $|E_q|$ is recognized entity count, $w_{\text{intent}} \in [0, 0.4]$ is intent-specific weight, and $\bar{c}_q$ is average recognition confidence.

Algorithm 1 Complexity-Based Inference Routing

Input: Query q, entities E_q, intent i, threshold $\tau = 0.3$
Output: Response r
$C \leftarrow$ ComputeComplexity(q, E_q, i)
$rules \leftarrow$ GetApplicableRules(E_q, i)
for $rule$ in $rules$ sorted by priority **do**
  if $rule$.CanApply(E_q, context) **then**
    $r_{local} \leftarrow rule$.Execute($E_q$, context)
  end if
end for
if $C \geq \tau$ **or** r_{local} is incomplete **then**
  $model \leftarrow$ ModelRouter.Select(TaskType)
  $r_{llm} \leftarrow$ Ollama.Generate(q, context, $model$)
  return Merge(r_{local}, r_{llm})
end if
return r_{local}

5.2 Task-Based Model Routing

The `ModelRouter` automatically selects optimal models based on task type:

Table 3: Task-based model preferences

Task Type	Preferred Models (in order)
SQL Generation	deepseek-coder, codellama, starcoder, qwen2.5-coder
Summarization	gemma3, gemma2, mistral, phi3, llama3.2
Reasoning	llama3.2, llama3.1, qwen2.5, gemma3, mistral
Classification	phi3, gemma2, llama3.2, mistral, qwen2.5
CAM Domain	llama3.2, qwen2.5, gemma3, mistral

Model selection uses a scoring formula:

$$\text{Score} = 0.3 \times \text{SuccessRate} + 0.5 \times \text{QualityScore} + 0.2 \times \text{LatencyScore} \tag{7}$$

where $\text{LatencyScore} = \max(0, 1 - \frac{\text{AvgLatency}}{10000})$. Scores are updated via exponential moving average from historical performance.

5.3 Three-Level LRU Cache

`ResponseCache` implements LRU caching with SHA256 key hashing:

Table 4: Cache configuration

Level	Capacity	TTL	Content
Query Cache	500	30 min	OntologyContext
Entity Cache	1000	60 min	Entity + Embedding
Inference Cache	200	30 min	InferenceResult

Overflow triggers LRU eviction of bottom 10%. Cache keys are normalized via lowercase conversion, whitespace normalization, and Korean particle normalization (/, /, /).

6 Experiments

6.1 Experimental Setup

Dataset: 150 real-world CAM tasks from Korean manufacturing companies, stratified by complexity:

- 60 turning operations (shafts, bushings) - Easy/Medium
- 50 milling operations (pockets, contours) - Medium
- 40 multi-axis operations (complex surfaces) - Hard

Evaluation Protocol: 5-fold stratified cross-validation with random seed 42. Statistical significance via paired t-test with Bonferroni correction. Effect sizes reported as Cohen's d.

Environment: Local deployment via Ollama on NVIDIA RTX 4090 (24GB VRAM). Models: Llama 3.2 (Q4_K_M), DeepSeek-Coder-V2 (Q4_K_M), Qwen 2.5 (Q4_K_M). SQLite 3.42 with FTS5. Python 3.11, .NET 8.0.

Metrics:

- **Setup Time**: Wall-clock time from query to executable CAM program
- **Process Accuracy**: Exact match of operation type sequence
- **Tool Accuracy**: Correct tool selection per operation
- **Condition Deviation**: MAPE of cutting parameters vs. expert

Baselines: Manual expert (15+ years), Rule-based KBM, GPT-4-turbo (zero-shot), Claude 3.5 Sonnet with vector-only RAG.

6.2 Main Results

Table 5: CAM task performance (mean $\pm$ std, 5-fold CV)

Method	Time (min)	Process Acc.	Tool Acc.	Cond. Dev.
Expert (manual)	32.4 ± 5.2	100%	100%	0%
Rule-based KBM	18.7 ± 3.1	$72.0 \pm 3.8\%$	$68.0 \pm 4.2\%$	$15.3 \pm 2.1\%$
GPT-4 (zero-shot)	24.1 ± 4.7	$61.0 \pm 5.2\%$	$54.0 \pm 6.1\%$	$23.7 \pm 4.3\%$
Claude 3.5 + RAG	19.8 ± 3.4	$78.0 \pm 3.1\%$	$71.0 \pm 3.8\%$	$12.1 \pm 2.4\%$
PMI-RAG (Ours)	$\mathbf{17.2 \pm 2.8}^{***}$	$\mathbf{89.0 \pm 2.4\%}^{***}$	$\mathbf{85.0 \pm 3.1\%}^{***}$	$\mathbf{7.4 \pm 1.8\%}^{***}$

$^{***}p < 0.001$ vs. all baselines (paired t-test, Bonferroni corrected)

Statistical Analysis: PMI-RAG achieves significant improvements:

- vs. Expert: 47.0% time reduction (95% CI: [42.1%, 51.9%], $d = 2.31$)
- vs. Claude 3.5 + RAG: +11% process accuracy ($p < 0.001$, $d = 1.42$)

- vs. GPT-4: +28% process accuracy ($p < 0.001$, $d = 2.87$)

Large effect sizes ($d > 0.8$) indicate practically significant improvements.

6.3 Ablation Study

Table 6: Component ablation with significance testing

Configuration	Process Acc.	Δ	p-value
Full PMI-RAG	$89.0 \pm 2.4\%$	—	—
− Ontology retrieval	$76.0 \pm 3.2\%$	-13.0%	< 0.001
− PMI extraction	$71.0 \pm 4.1\%$	-18.0%	< 0.001
− Hybrid (vector only)	$69.0 \pm 4.5\%$	-20.0%	< 0.001
− Local models (use GPT-4)	$82.0 \pm 3.0\%$	-7.0%	< 0.01
− Model routing (single model)	$83.0 \pm 2.9\%$	-6.0%	< 0.01
− Korean normalization	$81.0 \pm 3.1\%$	-8.0%	< 0.001

Key Findings: (1) Hybrid retrieval is critical (-20% without); (2) PMI extraction essential (-18%); (3) Local models outperform cloud GPT-4 by 7%, likely due to domain-specific fine-tuning potential; (4) Task-based model routing provides 6% gain.

6.4 Error Analysis

We analyzed all 17 failure cases (11% of 150 tasks):

Table 7: Failure taxonomy

Error Type	**Count**	**%**	**Root Cause**
Novel material	5	29.4%	Material not in ontology
Complex multi-setup	4	23.5%	Cross-setup dependencies
Ambiguous PMI	3	17.6%	Incomplete annotations
Entity recognition	3	17.6%	Korean abbreviation variants
LLM hallucination	2	11.8%	Plausible but unsafe params

6.5 Privacy and Latency Analysis

Table 8: Privacy and performance comparison

System	**Data Location**	**Avg Latency**	**Cost/Query**
GPT-4 API	Cloud (US)	2.1s	\$0.03
Claude API	Cloud (US)	1.8s	\$0.02
PMI-RAG (Local)	**On-premises**	**0.8s**	**\$0**

Local deployment via Ollama ensures: (1) Zero data egress—all CAD/CAM data remains on-premises; (2) 2.3× lower latency (no network round-trip); (3) Zero marginal cost per query.

7 Discussion

7.1 Limitations

- Multi-setup operations require human verification for safety
- Novel materials not in ontology produce suboptimal results
- Real-time tool wear adaptation not implemented
- Embedding search is $O(n)$; ANN indexing (HNSW) planned
- Current evaluation limited to 150 tasks; larger benchmarks needed

7.2 Broader Impact

Positive: PMI-RAG democratizes CAM expertise through faster onboarding, expert knowledge preservation, and reduced lead times. Privacy-preserving design enables adoption in sensitive industries.

Risks: Over-reliance on AI without human oversight in safety-critical applications. Mitigation: Commands with RiskLevel $\geq$ High require explicit user confirmation.

Economic: Estimated 47% reduction in setup time translates to \$11.75B annual savings industry-wide if adopted at scale.

8 Conclusion

We presented PMI-RAG, a universal ontology-based RAG agent for privacy-preserving CAM automation:

- **Manufacturing ontology**: 2,847 entities, 12,453 relations, 22 weighted relation types grounded in ISO standards
- **Hybrid retrieval**: 40% TF-IDF + 60% semantic with $O(|V| + |E|)$ graph traversal
- **Dual-path inference**: Complexity-based routing between local rules and LLM
- **Task-based model routing**: Automatic selection among DeepSeek, Llama, Qwen
- **Privacy-preserving**: 100% local deployment via Ollama

Results: 89% process accuracy ($p < 0.001$), 47% time reduction ($d = 2.31$), zero data egress.

Future Work: HNSW indexing for $O(\log n)$ embedding search, multi-CAM software support via standardized APIs, online learning from operator feedback, larger benchmark development.

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A Ontology Statistics

B Hyperparameters

Table 9: Entity distribution

Entity Type	Count	%
ToolEntity	1,247	43.8%
MaterialEntity	156	5.5%
OperationEntity	89	3.1%
CuttingConditionEntity	423	14.9%
CommandEntity	312	11.0%
FeatureEntity	620	21.8%
Total	**2,847**	100%

Table 10: System hyperparameters

Component	Parameter	Value
Hybrid Search	TF-IDF weight	0.4
	Embedding weight	0.6
	Min relevance	0.15
Graph Traversal	Max hops	3
	Decay factor α	0.7
	Max entities	20
Inference	Complexity threshold	0.3
	LLM temperature	0.3
	Max tokens	512
Cache	Query cache size	500
	Entity cache size	1000
	TTL	30 min

Paper Checklist

1. **Claims**

   Question: Do the main claims match the paper's contributions?

   Answer: [Yes]

   Justification: Claims (47% time reduction, 89% accuracy) supported by Tables 3-4 with statistical significance.

2. **Limitations**

   Question: Are limitations discussed?

   Answer: [Yes]

   Justification: Section 7.1 lists five specific limitations.

3. **Reproducibility**

   Question: Is reproducibility information provided?

   Answer: [Yes]

   Justification: Section 6.1 provides environment specs; Appendix B lists all hyperparameters; random seed 42 specified.

4. **Open access**

   Question: Will code/data be released?

   Answer: [Yes]

   Justification: Code and ontology will be released upon publication.

5. **Statistical Significance**

   Question: Are error bars and significance tests reported?

   Answer: [Yes]

Justification: All results report mean ± std, p-values with Bonferroni correction, and Cohen's d effect sizes.

6. **Compute Resources**

   Question: Are compute requirements specified?

   Answer: [Yes]

   Justification: RTX 4090 (24GB), Q4_K_M quantization, latency analysis in Table 6.

7. **Broader Impacts**

   Question: Are positive and negative impacts discussed?

   Answer: [Yes]

   Justification: Section 7.2 discusses democratization benefits and over-reliance risks with mitigation.

8. **Licenses**

   Question: Are licenses properly credited?

   Answer: [Yes]

   Justification: Llama 3 (Meta License), DeepSeek (MIT), Qwen (Apache 2.0), Ollama (MIT).