Enginuity: Building an Open Multi-Domain Dataset of Complex Engineering Diagrams

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Problem Statement

Engineering diagrams encode the core knowledge of scientific and technical disciplines but remain inaccessible to AI due to proprietary reasons. While current methods achieve 85%+ accuracy on symbol detection, they struggle with relationship extraction, the critical bottleneck where performance drops by 25%+ preventing true diagram understanding.

The Research Gap

- Currently no public dataset exists with >10K real-world engineering diagrams containing both component and structural relationship annotations.
- This gap prevents AI from participating in scientific workflows requiring visual-structural reasoning and system-level comprehension.

Solution: Enginuity Dataset

We propose ***Enginuity***: 50K annotated engineering diagrams starting with automotive domain (will be later expanded to include other domains) through our partnership with *Predii,* an automotive AI company processing 2B+ repair jobs monthly.

Why automotive diagrams?

Automotive diagrams are ideal: they combine visual structure, text, and functional knowledge in exploded parts diagrams used by technicians globally. ***Enginuity*** will enable three core AI tasks:

- **Component Detection:** Localize and classify fine-grained mechanical parts within dense assemblies, enabling models to recognize small, visually similar components at scale.
- **Relationship Extraction:** Identify functional and hierarchical links between parts (e.g., connections, attachments, dependencies) to recover the assembly's structural graph.
- **Diagram VQA:** Answer technical queries about diagrams (e.g., "Which part connects to X?" or "How many fasteners are used?") by jointly reasoning over visual layout and embedded text.

Evaluation

Metrics

Enginuity evaluates three task families using targeted metrics: detection quality, relational accuracy, and diagram-level retrieval performance, capturing localization, structural understanding, and technical Q&A over engineering diagrams.

Component Detection

$$detection = mAP@[.50:.95]$$
$$Recall = mAR$$
$$Classification\ Quality = F1_{macro}$$

Relationship Extraction

$$Hierarchy\ Accuacy = F1_{hierarchy}$$
$$Relation\ Ranking = nDCG@K$$
$$Graph\ Error = GED$$

- **Diagram VQA**

$$Retrieval\ Ranking = nDCG@K$$
$$Retrieval\ Precision = mAP@K$$

Data Collection

Two complementary sources ensure both openness and real-world relevance:

- **Public-Domain Automotive Diagrams**

We curate exploded parts diagrams and linked technical manuals from declassified government vehicles and older public-domain models. These diagrams include fine-grained assemblies (powertrain, chassis, body) and explicit cross-references to repair procedures. Domain experts from our industry partner perform structured human labeling.

- **Industry Engagement Framework**

We introduce a lightweight pathway for OEMs and suppliers to contribute **non-proprietary legacy diagrams (5–15 years old)** through our collaborator. Contributors share older, non-sensitive assets while benefiting from benchmarking insights and community visibility. This enables realistic, diverse data without exposing proprietary IP.

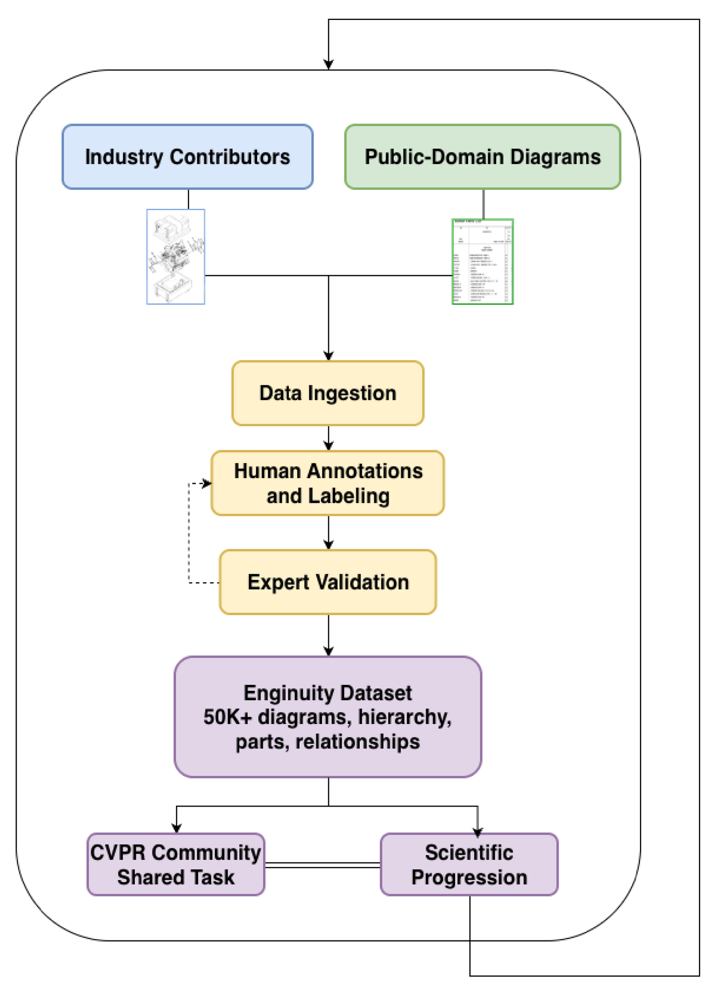

Figure (1) An overview of the Enginuity Data Collection Process

Dataset Examples

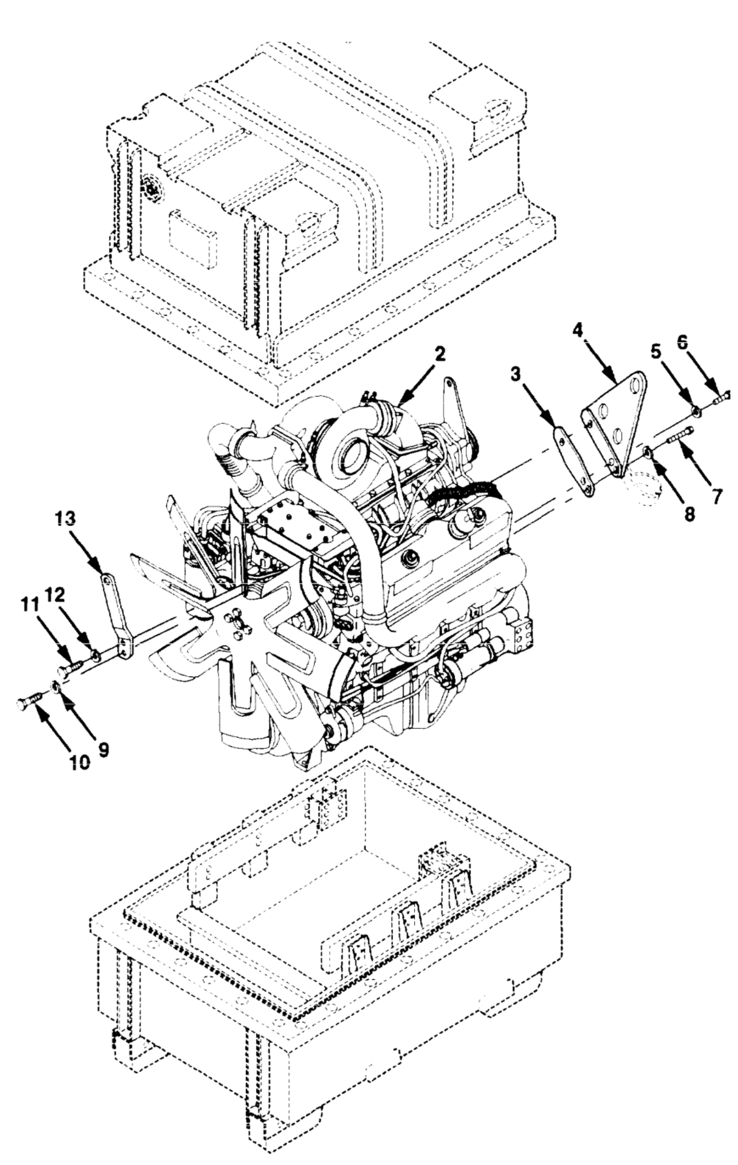

Figure (2) A parts explosion diagram for an engine block

. REPAIR PARTS LIST

(5) PART NUMBER	(6) DESCRIPTION USABLE ON CODE	(7) UM	(8) QTY INC IN UNIT
	GRDUP 0100 ENGINE ASSEMBLY		
57K3047	ENGINE/CONTAINER DDEC II	EA	1
57K4184	ENGINE/CONTAINER DDEC III	EA	1
12436583	. ENGINE ASSY, DRESSED DDEC II	EA	1
12472145	. ENGINE ASSY, DRESSED DDEC III ONLY	EA	1
5117332	..GASKET	EA	2
5133354	..BRACKET	EA	2
MS35338-8	..WASHER.LOCK 3/8	EA	1
5101377	..SCREW,CAP,HEX 3/8-16 X 1	EA	1
8921935	..BOLT,SELF-LOCKING 7/16-14 X 1 1/8	EA	2
MS35338-47	..WASHER,LOCK 7/16	EA	2
MS35338-48	..WASHER,LOCK 1/2	EA	1
MS35307-424	..SCREW,CAP,HEX 1/2-13 X 4 1/4	EA	I
223435	..SCREW,CAP,HEXAGON 5/8-11 X 1 3/4	EA	1
MS35338-50	..WASHER,LOCK 5/8	EA	1
8928612	..BRACKET,LIFT	EA	1

Figure (3) Associated Parts List for Figure (2)

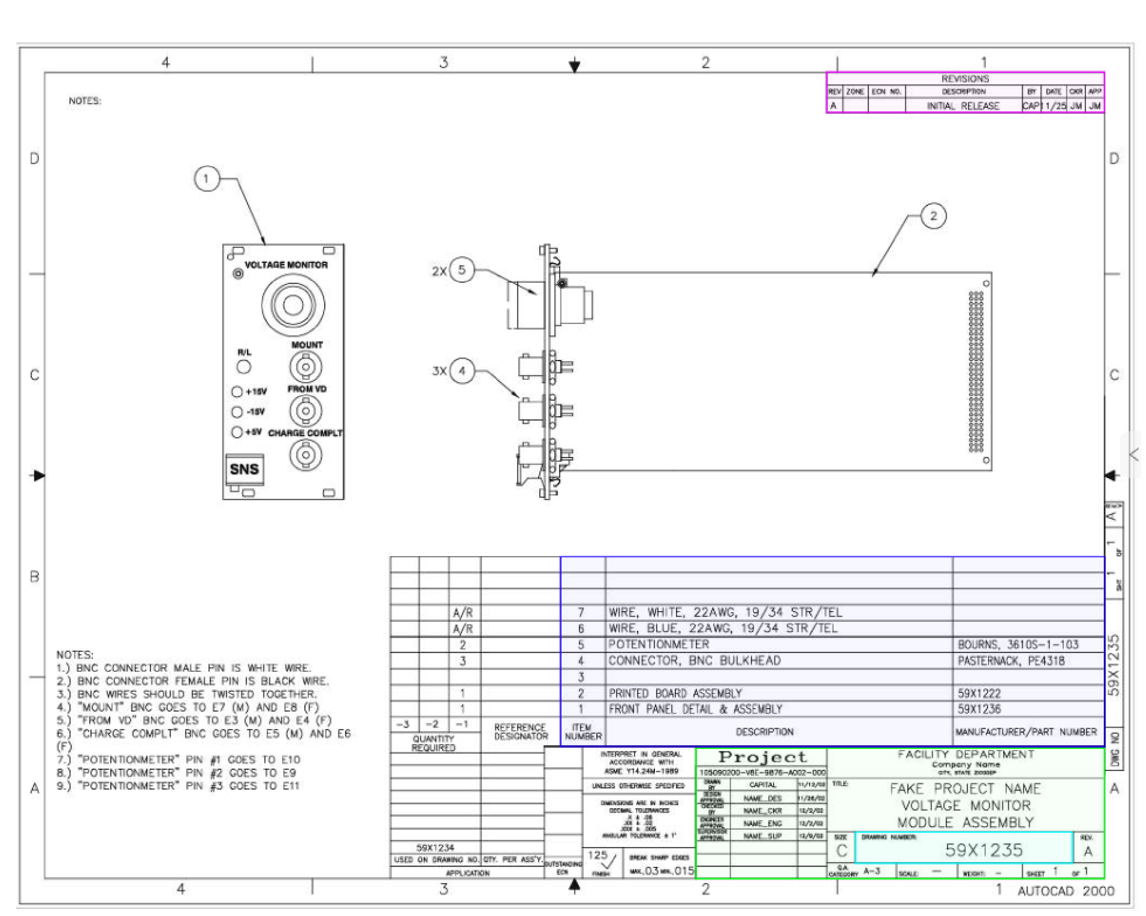

Figure (4) An example synthetic, annotated Engineering Schematic

Timeline & Impact

Released openly by Month 12 with 50K diagrams, Enginuity will transform AI's ability to understand complex engineering systems, enabling automated digital twin generation, design optimization, and knowledge preservation across domains.

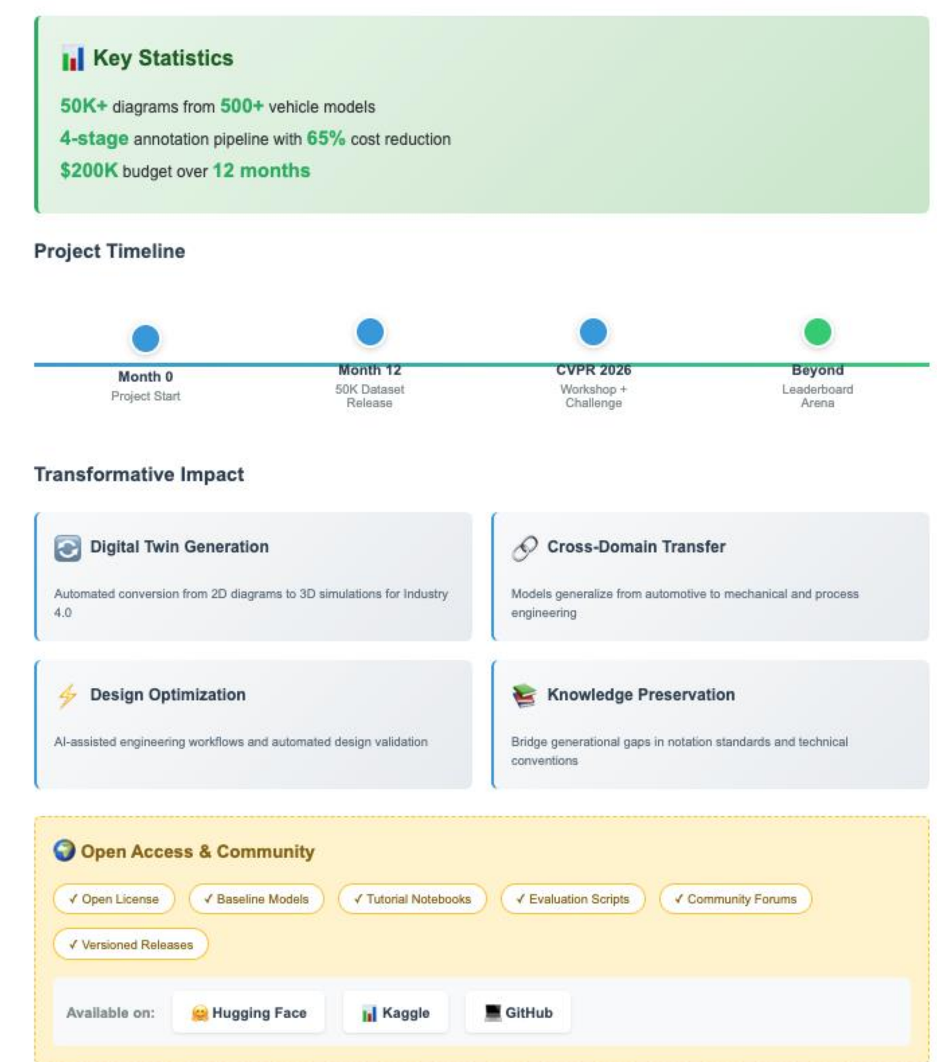

Figure (5) A visual diagram for the timeline and Impact of *Enginuity*

Initial Benchmarks

To evaluate initial dataset metrics, we benchmark SOTA LLMs on tasks requiring them to ground exploded diagrams to their corresponding parts lists. These questions are extremely difficult because models must perform fine-grained visual parsing, cross-reference part identifiers, and reason over mechanical structure.

Figure (6) An example query given to a LLM. LLMs and other models must learn to understand the relationship between the parts diagram and the explosion diagram.

Model	Part 43 name	Stator #	Hex nuts (total)	Parts connected to 43	Score (Q1–Q4)
Qwen 3 A3B (In)	Irreplace. Alternator ✗	45 ✗	15 ✗	3 ✓	1/4
Nemotron Nano	Stator ✓	43 ✓	9 ✗	5 ✗	2/4
Gemini 2.5 Flash	Stator ✓	43 ✓	11 ✗	2 ✗	2/4
Llama 4 Maverick	Stator ✓	43 ✓	11 ✗	8 ✗	2/4
GPT-5	Stator ✓	43 ✓	7 ✗	6 ✗	2/4
Claude Sonnet 4.5	Stator ✓	43 ✓	17 ✗	3 ✓	3/4
InternVL3	Stator ✓	43 ✓	24 ✗	3 ✓	3/4
Sonar	Stator ✓	43 ✓	13 ✓	0 ✗	**3/4**

Figure (7) Initial benchmarking highlights the difficulty of the task and underscores the need for Enginuity.

Conclusions

We propose **Enginuity**, a 50K+ diagram dataset built through a hybrid public+industry pipeline and a rigorous AI-assisted annotation workflow. Enginuity enables structured reasoning over real-world mechanical assemblies. Our work concludes with a CVPR shared task to catalyze open, community-driven progress.

Acknowledgments

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