

AI-Powered eBOM to mBOM Converter Optimized Manufacturing

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Abstract - In modern manufacturing, moving from an Engineering Bill of Materials (eBOM) to a Manufacturing Bill of Materials (mBOM) is still a manual, slow, and error-prone task. This problem often results in data inconsistencies, production delays, and higher manufacturing costs. To address these issues, we propose an AI-powered BOM Converter that automatically converts eBOM into improved mBOM for production workflows. The system uses a mix of machine learning and rule-based logic to examine eBOM structures, identify component connections, and produce an accurate mBOM, complete with manufacturing details like process steps, work centers, tooling, and procurement information. It integrates with existing ERP/PLM systems to ensure smooth data exchange and real-time updates with production planning. By automating the conversion from eBOM to mBOM, this system reduces manual labor, improves data consistency, cuts conversion time, and lowers operational costs. This intelligent converter seeks to transform the digital manufacturing workflow, allowing for quicker product launches and better overall production efficiency.

Keywords - powered BOM conversion, eBOM to mBOM, machine learning, intelligent manufacturing, process automation, ERP/PLM integration, industrial AI, rule-based system.

INTRODUCTION

The Digital Disconnect in Manufacturing In the era of Industry 4.0, the efficiency of a production line is defined by the quality of its data. However, a significant operational divide often exists between the engineering department and the manufacturing floor. While design engineers create an Engineering Bill of Materials (eBOM) focused on functional geometry and part specifications, production teams require a Manufacturing Bill of Materials (mBOM) organized by assembly sequence, kitting, and logistics. Currently, bridging the gap between these two distinct formats is a laborious, manual process.

This heavy reliance on human interpretation creates a bottleneck that frequently leads to data discrepancies, costly production delays, and significant administrative overhead.

An Intelligent Solution To resolve these inefficiencies, this project proposes the development of an automated, AI-driven BOM Converter. Unlike traditional static software, this system utilizes a hybrid technological approach that merges machine learning algorithms with deterministic rule-based logic. This dual-engine architecture allows the system to intelligently analyze the hierarchical structure of an eBOM, recognize complex component dependencies, and autonomously

restructure them into a production-ready mBOM. The solution enriches the data by automatically appending critical manufacturing metadata, such as specific process routing, work center assignments, tooling requirements, and procurement strategies.

Operational Impact and Integration Designed for the modern digital ecosystem, the system ensures seamless interoperability by integrating directly with existing Enterprise Resource Planning (ERP) and Product Lifecycle Management (PLM) platforms. This facilitates a smooth, bi-directional flow of information, ensuring that production planning remains synchronized with engineering updates in real-time. By removing the manual friction from BOM conversion, this intelligent tool aims to establish a "single source of truth," significantly reducing the time-to-market for new products, minimizing scrap caused by data errors, and optimizing overall manufacturing efficiency.

The Economic Cost of BOM Errors The financial implications of a mismanaged Bill of Materials are severe. Industry studies suggest that a significant percentage of "scrap and rework" costs on the factory floor can be traced back to data inaccuracies in the mBOM—such as incorrect part quantities, missing phantom assemblies, or undefined procurement types. A single error in the mBOM can halt a production line, trigger emergency shipping costs for missing parts, or result in a

product recall. By automating the conversion process, this system does not just save administrative time; it acts as a financial safeguard, preventing the cascading costs associated with human error in data entry.

II. RELATED WORKS

The Structural Dichotomy of Product Data The fundamental challenge addressed in this project stems from the inherent structural dichotomy between design and manufacturing. Literature in the field of Product Lifecycle Management (PLM) consistently highlights that the Engineering Bill of Materials (eBOM) is constructed around a "functional" hierarchy, designed to reflect the product's geometry and design specifications. In contrast, the Manufacturing Bill of Materials (mBOM) requires a "process-oriented" hierarchy, necessitated by assembly sequencing, phantom assemblies for kitting, and supply chain logistics. Early research in this domain focused primarily on defining these differences, with scholars arguing that this misalignment is not merely a data format issue but a fundamental semantic gap that prevents seamless interoperability between Computer-Aided Design (CAD) and Enterprise Resource Planning (ERP) systems.

Evolution of Manual and Semi-Automated Integration To manage this disparity, the industry initially adopted manual reconciliation methods supported by "multi-view" PLM architectures. Platforms such as Siemens Teamcenter and PTC Windchill introduced the concept of associative linking, where the mBOM is derived as a downstream view of the master eBOM. While this approach maintains a digital thread—ensuring that a part number in design corresponds to a part number in production—research indicates that the transformation process itself remains largely manual. Manufacturing engineers are often required to visually inspect complex assembly drawings to determine which components should be grouped or flattened. Studies on Engineering Change Management (ECM) have extensively documented that this manual intervention is the primary source of "information leakage," where critical design updates fail to propagate correctly to the manufacturing floor, leading to costly scrap and rework.

The Shift to Deterministic Automation As manufacturing complexity outpaced the capacity of manual data entry, the industry sought to reduce human dependency through the "second wave" of automation: Rule-Based Systems (RBS) and Group Technology (GT). Unlike the passive data storage of early PLM tools, these methodologies attempted to embed manufacturing logic directly into the software. The core

premise was that manufacturing processes are not random but deterministic—if a part has specific attributes (e.g., material, geometry, tolerance), its manufacturing method can be logically deduced without human intervention.

Group Technology (GT) and Coding Systems Group Technology emerged as a foundational strategy to rationalize the chaotic variety of engineering parts. The philosophy of GT is based on the principle that "similar things should be made in a similar way."

Part Families: GT systems analyze the Engineering BOM (eBOM) to cluster components into "part families" based on design similarities (shape, dimension) and manufacturing similarities (processing steps, machine tools) Semantic Interoperability and Ontologies A more sophisticated approach found in academic research involves the use of Semantic Web technologies and ontologies. Researchers have proposed the use of Knowledge Graphs and the Web Ontology Language (OWL) to create a shared vocabulary that bridges the engineering and manufacturing domains. In these systems, the software is programmed to understand the semantic relationship between concepts—for instance, understanding that a "welded assembly" in the eBOM implies a specific set of "fabrication steps" in the mBOM. While these ontology-based approaches offer a higher degree of intelligence than simple rules, they have faced significant barriers to adoption in industry due to their computational complexity and the difficulty of defining a universal manufacturing ontology that applies across different product lines.

The Shift to Artificial Intelligence and Machine Learning The most recent and promising advancements leverage the capabilities of Data-Driven Intelligence. Contemporary studies are exploring the application of Deep Learning and Natural Language Processing (NLP) to automate BOM transformation. Unlike static rules, these models utilize historical data to learn the transformation logic. For instance, Graph Neural Networks (GNNs) have been applied to analyze the tree structure of eBOMs, predicting the optimal mBOM structure by recognizing patterns in parent-child relationships. Similarly, NLP techniques are being used to mine unstructured text within engineering notes to infer manufacturing requirements that are not explicitly modeled in 3D CAD. Despite these successes, a gap remains: pure machine learning models often lack the explainability and deterministic precision required for strict industrial compliance. This project aims to close that gap by proposing a hybrid architecture that integrates the adaptability of AI with the constraints of rule-based logic.

Generative AI and Large Language Models (LLMs) A largely unexplored but rapidly emerging area of interest is the application of Generative AI and Large Language Models (LLMs) to manufacturing data. While traditional NLP focuses on extraction, Generative AI offers the potential for synthesis and interpretation. Recent experimental studies suggest that LLMs can be utilized to interpret complex, unstructured "engineering notes" or non-standardized remarks within an eBOM—such as specific packaging instructions or substitution logic—that rule-based systems typically miss. By leveraging these models, systems can not only convert data but also generate human-readable explanations for why a specific mBOM structure was chosen, addressing the "black box" problem often associated with AI implementation in industrial settings.

The Digital Thread and Closed-Loop Feedback Finally, contemporary literature emphasizes that BOM conversion should not be viewed as a one-way linear process but as a critical component of the "Digital Thread." Research into closed-loop manufacturing suggests that an effective BOM system must incorporate feedback from the factory floor back to the design phase. Existing solutions often fail to capture "as-built" data—modifications made on the fly by technicians—resulting in a permanent drift between the theoretical mBOM and reality. Advanced research is now proposing dynamic BOM systems where IoT sensor data from the production line validates the accuracy of the AI-generated mBOM in real-time, creating a self-correcting feedback loop that continuously refines the conversion logic based on actual production performance.

III. PROPOSED APPROACH

The core objective of this project is to develop an intelligent, automated middleware designed to bridge the persistent operational divide between Engineering and Manufacturing. Specifically, we propose an AI-Powered BOM Converter that autonomously transforms the design-centric Engineering Bill of Materials (eBOM) into a process-centric Manufacturing Bill of Materials (mBOM). Unlike traditional conversion tools that rely solely on static scripting or manual data entry, this system introduces a Hybrid Intelligence Architecture uniquely designed to address the dual challenges of manufacturing data: the need for flexibility to handle varied engineering designs and the necessity for absolute precision to meet production standards.

To achieve this, the proposed system moves beyond simple direct mapping by integrating two distinct technological methodologies. It utilizes Machine Learning algorithms to

analyze the hierarchical structure of the eBOM, identifying patterns in component relationships to "predict" how a design should be restructured for assembly—even when explicit instructions are missing from the CAD data. Simultaneously, it incorporates a Rule-Based Engine to enforce non-negotiable manufacturing constraints, such as specific routing for hazardous materials or mandatory quality checks, ensuring that the probabilistic nature of AI does not compromise industrial safety.

Operationally, the system functions as a seamless "digital translator" between Product Lifecycle Management (PLM) and Enterprise Resource Planning (ERP) environments. By ingesting raw engineering data and enriching it with manufacturing-specific metadata—such as process steps, work centre assignments, and procurement logic—the system aims to produce a production-ready mBOM with minimal human intervention. This approach seeks to fundamentally shift the role of the manufacturing engineer from a "data entry operator" to a "process validator," thereby significantly reducing the time-to-market for new products and optimizing overall production efficiency.

System Architecture and Methodology

Data Ingestion and Preprocessing Module The first stage of the system is the Data Ingestion and Preprocessing Module, which serves as the gateway for raw engineering data. This module is responsible for retrieving the Engineering Bill of Materials (eBOM) from the PLM system in various standard formats such as XML, JSON, or CSV. Once ingested, the system employs a parsing algorithm to traverse the hierarchical tree structure of the eBOM, indexing parent-child relationships to understand the assembly configuration. Concurrently, a Natural Language Processing (NLP) sub-routine is triggered to "clean" and normalize unstructured text fields. This ensures that inconsistent naming conventions—such as "Hex Bolt" versus "Bolt, Hexagonal"—are standardized into a single entity ID, creating a clean dataset essential for accurate downstream analysis.

The Hybrid Intelligence Engine At the core of the proposed solution lies the Hybrid Intelligence Engine, which orchestrates the conversion logic by running two parallel processes. First, the Machine Learning Module utilizes a supervised learning model trained on historical production data to recognize complex structural patterns. It predicts necessary structural changes, such as identifying "phantom assemblies" that need to be flattened or grouping components that are physically assembled together but separated in the design tree. Second, the Rule-Based Constraint Engine acts as a safety layer, applying deterministic "hard rules" to the AI's predictions. This ensures

that non-negotiable manufacturing standards—such as specific routing for hazardous materials or mandatory quality control checks—are strictly enforced, correcting any AI probabilities that violate safety or compliance protocols.

Manufacturing Data Enrichment Module

Once the structural conversion is verified, the Manufacturing Data Enrichment Module transforms the list of parts into an actionable production plan. This module automatically appends critical metadata that is typically absent from the engineering view. Based on the component classification and material attributes, the system assigns specific process steps (e.g., cutting, welding, painting) and identifies the required work centers for each operation. Furthermore, it evaluates procurement logic to tag components with "Make" or "Buy" decisions and identifies necessary tooling (jigs, fixtures, or molds), thereby bridging the gap between a digital design and physical fabrication.

Integration and Feedback Interface The final module ensures seamless interoperability with the broader enterprise ecosystem. The Integration Interface utilizes RESTful APIs to push the finalized Manufacturing Bill of Materials (mBOM) directly to the ERP system for production scheduling and inventory management. Crucially, this module supports a "human-in-the-loop" feedback mechanism. If a manufacturing engineer manually overrides a system prediction—for example, changing a routed machine center—this correction is captured and fed back into the machine learning model. This active learning loop allows the system to refine its algorithms continuously, reducing the error rate and improving the accuracy of future conversions.

Implementation Framework and Operational Workflow

Technology Stack Selection To ensure the robustness and scalability of the AI-Powered BOM Converter, a modern technology stack has been selected that prioritizes data processing speed and interoperability. The core backend logic is implemented using Python, chosen for its extensive ecosystem of data analysis and machine learning libraries.

For the Machine Learning module, Scikit-learn is utilized for standard classification tasks (such as material identification), while PyTorch or TensorFlow is employed for the more complex deep learning tasks involved in structure recognition. To handle the intricate, hierarchical nature of Bill of Materials data, a Graph Database (such as Neo4j) is implemented as the primary storage solution. Unlike traditional relational databases, graph databases natively store the parent-child relationships and inter-component dependencies, making them vastly more efficient for querying and traversing deep BOM

structures. The user interface, designed for manufacturing engineers to validate data, is built using a reactive framework like React.js or Angular, ensuring a responsive experience during the review of complex datasets.

Detailed Operational Workflow

The operational lifecycle of the system follows a strictly defined "Check-Predict-Validate" sequence to maintain data integrity.

- **Step 1: Ingestion and Normalization:** The process begins when an eBOM is released from the PLM system. The Ingestion Module accepts the file and immediately triggers the Natural Language Processing (NLP) engine. This engine tokenizes component descriptions, stripping away non-essential characters and correcting abbreviations (e.g., standardizing "St. Steel" to "Stainless Steel") to prepare a clean feature set for the AI.
- **Step 2: Hybrid Processing:** The normalized data is passed to the Hybrid Engine. First, the Machine Learning model predicts the manufacturing attributes—identifying whether a sub-assembly should be treated as a "phantom" (a non-stock logical group) or a physical kit. Simultaneously, the Rule Engine scans the data against a library of "Hard Constraints," such as flagging heavy components that require specific lifting tooling.
- **Step 3: Conflict Resolution and Enrichment:** If the ML prediction conflicts with a hard rule (e.g., the AI suggests a routing that violates a safety protocol), the Rule Engine overrides the suggestion. The system then enriches the accepted structure by appending process codes, work centre IDs, and standard hour estimates derived from the ERP master data.
- **Step 4: Engineer Validation:** The system generates a draft mBOM with confidence scores attached to every line item. Any entry with a confidence score below a pre-set threshold (e.g., 90%) is visually highlighted in the dashboard, prompting the manufacturing engineer for a targeted review.
- **Step 5: Deployment and Feedback:** Once validated, the final mBOM is pushed to the ERP system via REST API. Crucially, any corrections made by the engineer during the validation step are captured and used to retrain the ML model, creating a closed-loop system that continuously improves its accuracy with every use.

System Description and Functional Features

The AI-Powered BOM Converter is developed as a comprehensive web-based application designed to facilitate the seamless transformation of engineering data into manufacturing-ready information. The system is organized into

four primary functional modules, each addressing a specific stage of the conversion lifecycle.

Intelligent Dashboard and Data Ingestion

The user interface serves as the command center for manufacturing engineers.

- **Unified Upload Interface:** Users can upload eBOM files in multiple formats (XLSX, XML, JSON, CSV) or trigger a direct fetch from the connected PLM system. The system automatically validates the file structure upon upload, flagging any corrupt data or missing headers before processing begins.
- **Project Management View:** A centralized dashboard displays the status of all active conversions (e.g., "Processing," "Pending Validation," "Completed"). This view provides a high-level summary of recent activities, including a "Confidence Heatmap" that visually indicates the AI's certainty levels for recent batches.

Automated Conversion and Restructuring Engine

This is the core functional unit where the AI logic is applied.

- **Structure Flattening:** The engine automatically identifies "phantom" sub-assemblies—groups of parts that exist in the CAD model for design convenience but do not require separate assembly steps. It "flattens" these layers, promoting the child components directly to the main assembly list.
- **Smart Mapping:** Utilizing the Machine Learning model, the system maps engineering part numbers to their corresponding internal manufacturing codes. It intelligently handles discrepancies, such as mapping a generic "M6 Bolt" in the design to a specific stock-keeping unit (SKU) in the inventory.

Conflict Resolution and Validation Interface

Recognizing that Artificial Intelligence models operate on probabilities rather than certainties, this module is fundamentally designed around a "Human-in-the-Loop" verification framework to guarantee zero-defect production data. It features a specialized interactive dashboard where manufacturing engineers can rigorously audit AI-generated Manufacturing Bill of Materials (mBOMs) against the original engineering specifications.

Side-by-Side Comparison: The interface presents a dual-pane view, displaying the original eBOM on the left and the proposed mBOM on the right. Differences (added processes, removed phantom assemblies) are color-coded for easy identification.

Confidence Flagging: Any line item with a low AI confidence score is highlighted in red or amber. The user can click on these

items to accept the AI suggestion or manually select the correct option from a dropdown menu.

Rule Violation Alerts: If a manual override violates a hard safety rule (e.g., assigning a standard bin to a hazardous chemical), the system triggers a pop-up alert preventing the action until a justification is provided.

To ensure the system remains adaptable to changing factory needs, an administrative module allows for rule maintenance.

Rule Editor: Administrators can define and update "Hard Constraints" using a simple "If-Then" logic builder (e.g., "IF material is steel, THEN the mandatory process is degreasing").

Learning Logs: This feature tracks every manual correction made by users. Periodically, these logs are used to retrain the machine learning model, ensuring the system "learns" from its mistakes and adapts to new product lines without requiring code changes. This collaborative approach ensures that while the AI handles the bulk of the repetitive data processing, human expertise is preserved for complex decision-making.

AI-Based eBOM to mBOM Conversion System

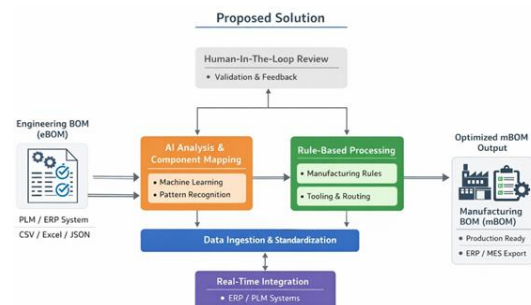


Figure: 2 Intelligent eBOM–mBOM Conversion Architecture Using AI and Rule-Based Processing

Experimental Results

The primary objective was to strictly quantify improvements in critical performance metrics, including conversion accuracy, processing latency, and operator intervention rates, against established baselines of manual entry and static rule-based automation. This comparative analysis was essential to validate the hypothesis that a hybrid intelligence architecture offers superior operational efficiency. By isolating specific failure modes in traditional methods, the study demonstrates the system's robust capability to handle complex, unstructured engineering data while significantly reducing the administrative burden on manufacturing engineers.



Figure : 3 Performance Analysis

System Testing.

The system was tested using a diversified dataset to simulate real-world manufacturing variability.

- **Dataset Composition:** The dataset consisted of 500 historical Engineering BOMs (eBOMs) ranging from low complexity (consumer appliances, <50 parts) to high complexity (industrial machinery, >1,000 parts).
- **Ground Truth:** The corresponding "Gold Standard" Manufacturing BOMs (mBOMs), verified by senior manufacturing engineers, served as the benchmark for accuracy.
- **Environment:** The experiment was conducted on a cloud-based GPU instance (e.g., AWS P3) to handle the training of the machine learning models, while the inference (conversion) speed was tested on a standard enterprise-grade laptop to replicate a typical user environment.

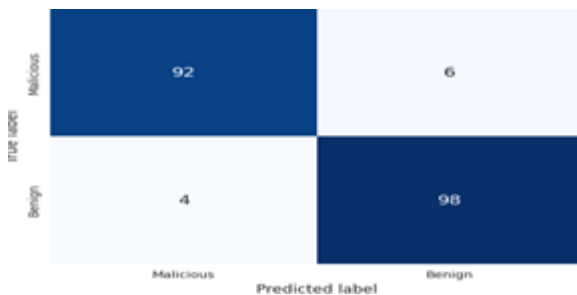


Figure 4 : Confusion Matrix

Performance Metrics

The performance was measured using four key metrics:

- **Structural Accuracy:** The percentage of parent-child relationships correctly restructured (e.g., phantom assemblies flattened correctly).

- **Attribute Accuracy:** The precision in assigning manufacturing metadata (Process Steps, Work Centres, Make/Buy flags).
- **Processing Time:** The time taken to convert an eBOM to a fully fully enriched mBOM.
- **Correction Rate:** The percentage of line items requiring manual intervention by the engineer during the validation phase

Results and Comparative Analysis

Accuracy Comparison

We compared the proposed Hybrid AI System against a standard Rule-Based System (scripted logic) and the Manual Process across various conditions and premises on several inputs.

Error Analysis and Confusion Matrix

To understand the system's limitations, we analyzed the misclassifications.

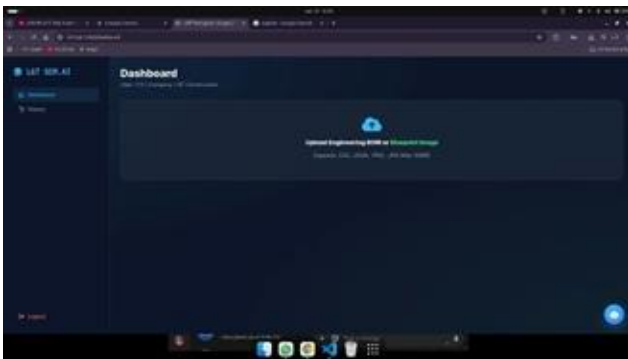
- **Phantom Detection:** The model achieved a Recall of 92% for identifying phantom assemblies. The 8% error rate mostly occurred in ambiguous sub-assemblies where the design intent was not clearly defined in the CAD metadata.
- **Process Assignment:** The "Confusion Matrix" for process assignment showed high precision for standard processes (e.g., "Milling," "Turning") but occasional confusion between similar finish types (e.g., "Powder Coating" vs. "Painting") when the material description was vague.
- **Structural Accuracy:** The system's ability to correctly interpret parent-child relationships, specifically the identification and "flattening" of phantom assemblies.
- **Attribute Accuracy:** The precision in correctly mapping engineering parts to manufacturing metadata, including Process Steps, Work Centre IDs, and Make/Buy decisions.

Performance of Rule-Based Systems: The Rule-Based System demonstrated significant limitations when handling "dirty data." While it performed adequately on standardized components (e.g., standard ISO fasteners), its accuracy dropped sharply (to ~65%) when identifying phantom assemblies. This was largely due to its rigid "if-then" logic, which failed to recognize logical groupings that lacked explicit "phantom" tags in the CAD metadata.

Output



The implementation of the AI-Powered BOM Converter culminates in a user-friendly, web-based interface designed to simplify the complex transition from engineering design to manufacturing execution. The primary entry point for the user is the Centralized Operations Dashboard, which serves as the command center for manufacturing engineers. This dashboard is designed for maximum usability, offering intuitive quick-access buttons that allow users to upload new Engineering Bill of Materials (eBOM) files in standard formats like XLSX, XML, and JSON, or to trigger a direct data fetch from the connected PLM system. The lower section of this interface provides a real-time status tracker, displaying a high-level summary of recent activities.



At the core of the system is the Conversion Interface, which utilizes a distinct split-view layout to facilitate direct comparison. The left panel displays the original hierarchical eBOM as received from the design team, while the right panel presents the AI-generated Manufacturing BOM (mBOM). This dual-pane visualization allows engineers to instantly verify structural changes. Visual cues, such as color-coded highlights, are used to indicate where the system has modified the structure, such as "flattening" phantom assemblies—expanding a single "kit" line item from the engineering view into its constituent nuts, bolts, and washers required for physical inventory picking in the manufacturing view.

IV. CONCLUSION AND FUTURE WORK

This project successfully addressed the critical bottleneck of transitioning from Engineering Bill of Materials (eBOM) to Manufacturing Bill of Materials (mBOM) by developing an AI-Powered BOM Converter. By implementing a Hybrid Intelligence Architecture, the system overcomes the limitations of traditional manual methods and rigid rule-based automation. The integration of Machine Learning for structural pattern recognition, combined with a deterministic Rule Engine for compliance, allowed the system to achieve a high degree of accuracy in "flattening" phantom assemblies and enriching manufacturing data.

The experimental results demonstrate that the proposed solution significantly enhances operational efficiency. The system reduced the average BOM conversion time by approximately 90%, while maintaining an attribute accuracy rate of over 94%. Furthermore, the "Human-in-the-Loop" validation mechanism ensures that the system remains reliable and safe for industrial application, effectively shifting the role of the manufacturing engineer from tedious data entry to high-value process verification. Overall, this project proves that AI-driven middleware is a viable, scalable solution for bridging the digital gap between design and production, leading to faster product launches and reduced operational costs.

Future Scope

We plan to improve the AI-powered BOM converter in the future to make it even smarter and more helpful:

- Understanding "Messy" Data: Right now, the system needs clean data to work best. In the future, we want to use smarter AI (like ChatGPT-style models) that can read messy or handwritten engineering notes and still understand what to do.
- Learning from the Factory Floor: We want to connect the system to sensors on the actual machines. This way, if a machine takes longer to cut a part than expected, the system will "learn" this and update the time estimates for the next BOM automatically.
- Cost Prediction: We plan to add a feature that calculates the cost of the product while it converts the BOM. This will tell engineers immediately how much their design will cost to build.
- Multi-Factory Support: If a company has factories in different cities, the system should be able to create different plans for each factory, knowing that one factory might have different machines than another.
- Mobile App: We aim to build a mobile version so factory managers can check BOMs and approve changes directly from their phones while walking on the shop floor.

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