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Smart Product Design Assistance Using Nlp And Ml

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ABSTRACT

In the modern customer-driven market, the demand for customized products has increased significantly. However, traditional product design methods rely heavily on expert knowledge, manual planning, and repeated trial-and-error processes, making customization time-consuming and costly. This paper presents a Smart Product Design Assistance System using Artificial Intelligence, Machine Learning, and Natural Language Processing (NLP) to support automated and structured customized product design. The system accepts user requirements in textual form and applies NLP techniques to extract meaningful design features, which are further analyzed using machine learning models to map the input to predefined product design and manufacturing workflows. Based on this analysis, the system generates structured end-to-end manufacturing guidance, including raw material selection, required tools, design considerations, step-by-step manufacturing procedures, cost estimation, and safety guidelines. The proposed system focuses on accurate and well-structured text-based guidance rather than image generation, ensuring clarity and reliability. By storing expert knowledge in a centralized knowledge base and automating design-related decision-making, the system reduces dependency on human experts, minimizes errors, and shortens the product development cycle, making customized product design more accessible for educational and small-scale manufacturing environments.

KEYWORDS

Artificial Intelligence (AI), Natural Language Processing (NLP), Machine Learning (ML), Customized Product Design, Intelligent Design Assistance, Knowledge-Based System, Smart Manufacturing, Manufacturing Process Planning, Text-Based Requirement Analysis, Automated Manufacturing Guidance, Product Concept Generation, AI-Assisted Design System, Design Automation, Intelligent Decision Support, Digital Product Development, Human-AI Collaboration in Design, Smart Design Workflow, Intelligent Engineering Systems.

I. Introduction

In the present era, product design and manufacturing planning are increasingly supported by intelligent digital technologies to satisfy evolving user expectations and competitive market demands. Despite this progress, many existing design support systems continue to rely on conventional workflows that demand significant manual input and continuous expert involvement. Consequently, designers and manufacturers frequently encounter issues such as extended design cycles, elevated development costs,

restricted customization capabilities, and difficulties in converting conceptual ideas into practical manufacturing procedures. These challenges underline the necessity for advanced systems capable of automating design assistance while enhancing feasibility and operational efficiency. The Smart Product Design Assistance System based on NLP and Machine Learning is developed to overcome these constraints by offering an interactive, AI-enabled platform for customized product design. The system allows users to express their design requirements in natural language and produces optimized design recommendations together with viable manufacturing steps. Through the analysis of user intent, design limitations, and previously recorded manufacturing data, the system independently supports concept development and process planning. This methodology reduces manual workload, enhances the precision of design outcomes, and promotes faster as well as more cost-efficient product development within contemporary manufacturing environments.

II. Problem Statement

Modern product design and manufacturing consist of several interconnected stages, including requirement analysis, conceptual development, material selection, feasibility assessment, and process planning. Many currently available product design systems depend significantly on manual expertise and rigid predefined workflows, which frequently lead to longer design cycles, increased development expenses, and restricted customization options. Designers and manufacturers are often required to utilize multiple software tools or seek guidance from domain specialists to transform user requirements into workable product designs and corresponding manufacturing procedures. Although certain computer-aided design and automation solutions are available, they generally demand technical proficiency and do not facilitate interaction through natural language. Such systems lack the capability to intelligently interpret user intent, recognize design constraints, and evaluate real-world manufacturing feasibility. Consequently, they are unable to deliver adaptive design recommendations, optimized alternatives, or automated process planning. Furthermore, existing approaches do not adequately incorporate machine learning-driven decision-making to minimize human intervention and enhance operational efficiency. Therefore, there is a clear need for an intelligent, automated, and user-friendly system that enables individuals to specify product requirements in natural language while producing practical and optimized design and manufacturing solutions. The Smart Product Design Assistance System utilizing NLP and Machine Learning combines natural language processing techniques, intelligent recommendation mechanisms, and data-driven evaluation to deliver precise design support and accurate prediction of manufacturing steps.

III. Existing System

In the current system, product design and customization are mainly performed through conventional approaches that depend greatly on expert knowledge and manual planning procedures. Designers and engineers interpret user requirements based on their previous experience and rely on trial-and-error strategies to arrive at finalized product designs. This method generally includes multiple rounds of testing, modification, and validation, which require substantial time and contribute to higher development expenses. Since customized product design demands ongoing expert participation, it becomes challenging for beginners, students, and small-scale manufacturers to engage effectively in the process.

Additionally, the existing system does not provide sufficient automation or structured support for manufacturing activities. Critical design choices such as selecting appropriate materials, identifying necessary tools, and evaluating process feasibility are largely influenced by personal judgment, which can result in inconsistencies and potential human errors. Because expert knowledge is not maintained within a centralized repository, opportunities for knowledge reuse are minimal, and design results often vary according to the experience level of the designer. As a consequence, the complete product development cycle tends to be slow, costly, and less accessible to a wider range of users.

Challenges in Existing Systems

- Strong reliance on domain specialists and expert intervention
- Lengthy and repetitive trial-and-error design procedures
- Increased expenses in development and customization
- Insufficient level of automation in design workflows
- Variability and inconsistency in design decision-making
- Minimal scope for effective knowledge use
- Limited accessibility for beginners and small-scale industries
- Extended duration of the overall product development cycle
- Greater possibility of human-induced errors

IV. Proposed System

The proposed AI-Based Customized Product Design Assistance system presents an intelligent and automated solution designed to address the limitations of traditional product design methods. It enables users to submit product requirements in textual format, ensuring accessibility for both technical professionals and non-technical individuals. Natural Language Processing techniques are applied to analyze and preprocess the input text, allowing the system to extract relevant design features and interpret user intent effectively.

After extracting the required information, machine learning models analyze the identified features and map them to suitable product design structures and manufacturing workflows stored within the system database. Based on this analysis, the system generates a structured manufacturing guide that includes raw material selection, required tools, design specifications, and detailed step-by-step manufacturing procedures. This automated process helps users clearly understand how a product idea can be transformed into a practical and manufacturable design.

In addition, the system maintains a centralized knowledge base that stores expert design knowledge, manufacturing standards, and safety guidelines to ensure consistency and reliability in generated outputs. By automating major design-related decisions, the system minimizes human dependency, reduces design errors, and improves overall efficiency in product development. As a result, the proposed system makes customized product design more accessible, scalable, and suitable for educational, industrial, and real-world manufacturing applications.

V. Methodology

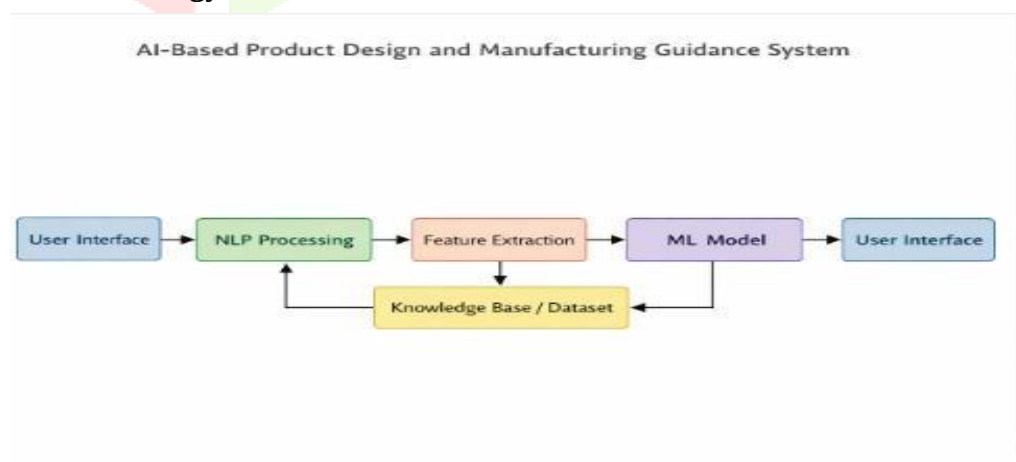


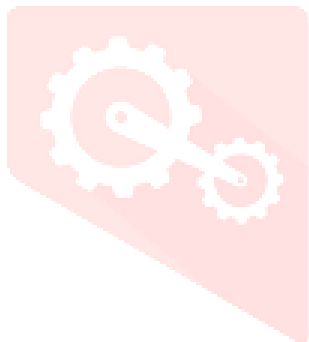
Fig.1: Process Flow

The proposed system adopts a well-defined methodology that combines Natural Language Processing (NLP) and Machine Learning (ML) techniques to deliver intelligent support for customized product design. The overall process is organized into several stages to guarantee precise interpretation of user requirements and dependable generation of manufacturing guidance. At the beginning, the user submits

product requirements in free-form textual format, describing preferred features, dimensions, material choices, and functional constraints. This input is processed through NLP techniques including tokenization, stop-word elimination, lemmatization, and part-of-speech tagging to refine and standardize the text. Subsequently, keyword extraction and named entity recognition are utilized to detect essential parameters such as product category, dimensional limits, material specifications, and intended usage conditions.

After preprocessing, meaningful feature representations are derived from the refined text using representation methods such as Term Frequency–Inverse Document Frequency (TF-IDF) and meaningful feature representations are derived from the refined text using Term Frequency–Inverse Document Frequency (TF-IDF) vectorization. These extracted features are then supplied to machine learning models that categorize the product appropriately and determine suitable design and manufacturing workflows. Supervised learning techniques, including Random Forest classifier, are applied to evaluate user requirements, while rule-based reasoning mechanisms are employed to verify design feasibility. A centralized knowledge base serves a significant function within this framework by storing expert design principles, material characteristics, manufacturing limitations, cost considerations, and safety regulations. The outputs generated by the ML models are aligned with this knowledge repository to obtain relevant design templates and process instructions. A decision engine consolidates insights from NLP processing, ML predictions, and knowledge base rules to produce a coherent and feasible manufacturing strategy.

In the final stage, the system produces a structured textual response containing material recommendations, required tools, design considerations, detailed step-by-step manufacturing instructions, estimated cost analysis, and safety guidelines. The generated results are examined to ensure logical consistency and practical applicability before being delivered to the user. This comprehensive methodology promotes automation, precision, scalability, and minimized reliance on human expertise in customized product design assistance.



System Architecture

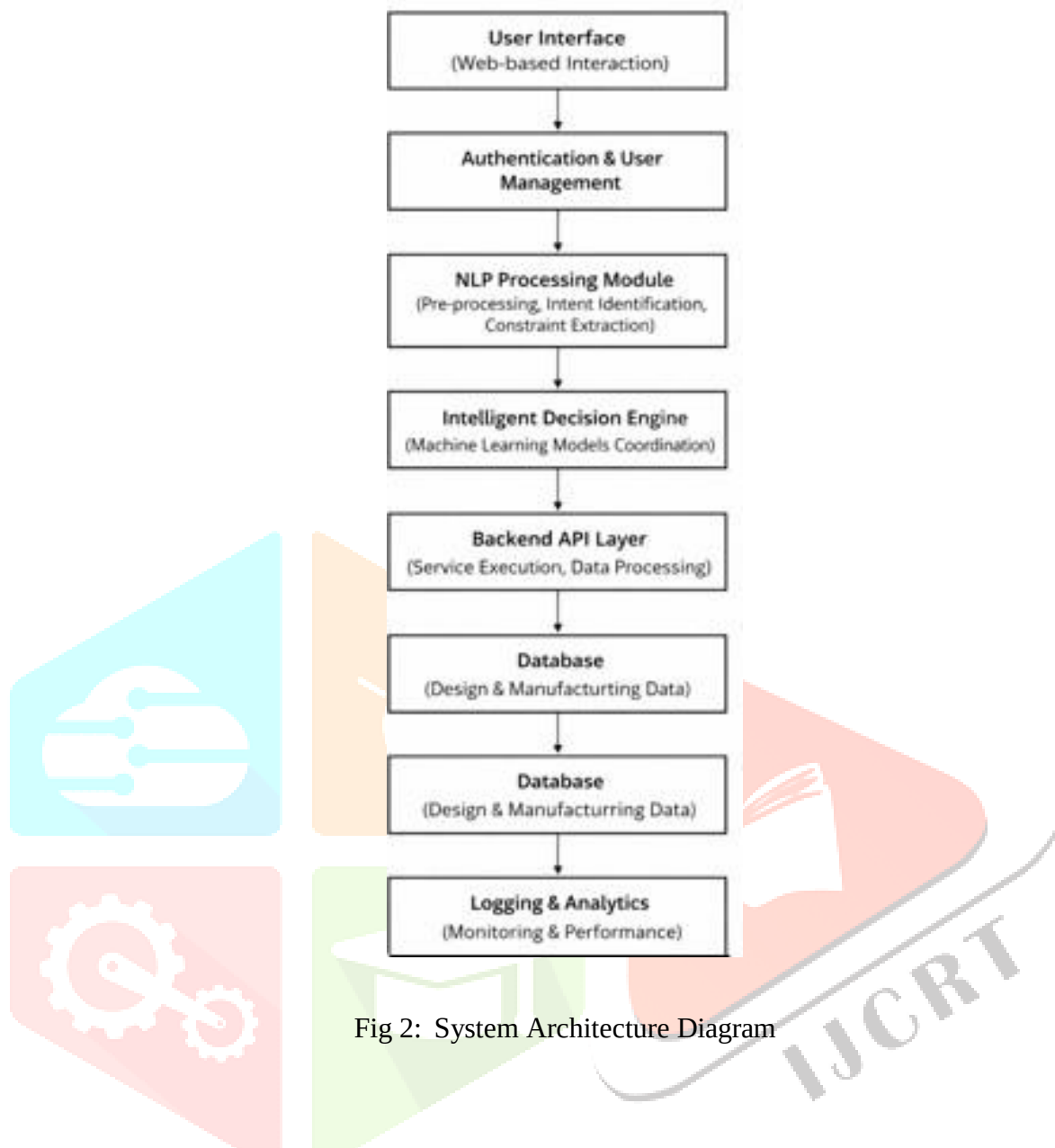


Fig 2: System Architecture Diagram

The proposed Smart Product Design Assistance System based on NLP and Machine Learning is designed using a layered architecture to facilitate intelligent interaction, effective design evaluation, and accurate manufacturing step prediction. The overall system is composed of several key components, including a user interface, authentication and access control module, natural language processing unit, intelligent decision engine, backend services layer, and a centralized database. Users engage with the system through a web-based interface where they submit product requirements in natural language format. The authentication and user management module ensures secure access to system functionalities and protects stored information.

The NLP module is responsible for performing text preprocessing, identifying user intent, and extracting relevant constraints from the submitted input. The intelligent decision engine interprets these extracted details and collaborates with machine learning models to produce practical design recommendations and optimized manufacturing procedures. The backend API layer manages service execution, data handling, and communication with the centralized database, which maintains product design records, user information, and historical manufacturing data. The final design outputs and manufacturing guidance are displayed to the user through the interface, while system operations are continuously monitored and recorded using logging and analytics modules to support evaluation and ongoing performance improvement.

System Workflow

The system workflow outlines the complete sequence of operations carried out from the moment a user interacts with the platform to the final generation of design and manufacturing recommendations. At the initial stage, the user accesses the application through the web-based interface and logs in with valid credentials. The authentication module verifies the user's identity and grants secure access to the available design functionalities. Once authentication is successful, the user provides product requirements in natural language format.

The NLP processing module then examines the submitted input by conducting text preprocessing, recognizing user intent, and extracting relevant constraints. The identified information is transmitted to the intelligent decision engine, which assesses the requirements and activates suitable machine learning models to generate design suggestions and predict corresponding manufacturing steps. The backend service layer manages these operations and communicates with the centralized database to retrieve past design records and store newly produced outputs. Subsequently, the system delivers optimized design recommendations along with feasible manufacturing procedures to the user via the interface. In the final stage, all user activities and system processes are documented within the logging and analytics module to enable monitoring, evaluation, and ongoing enhancement of system performance.

Proposed System Algorithm

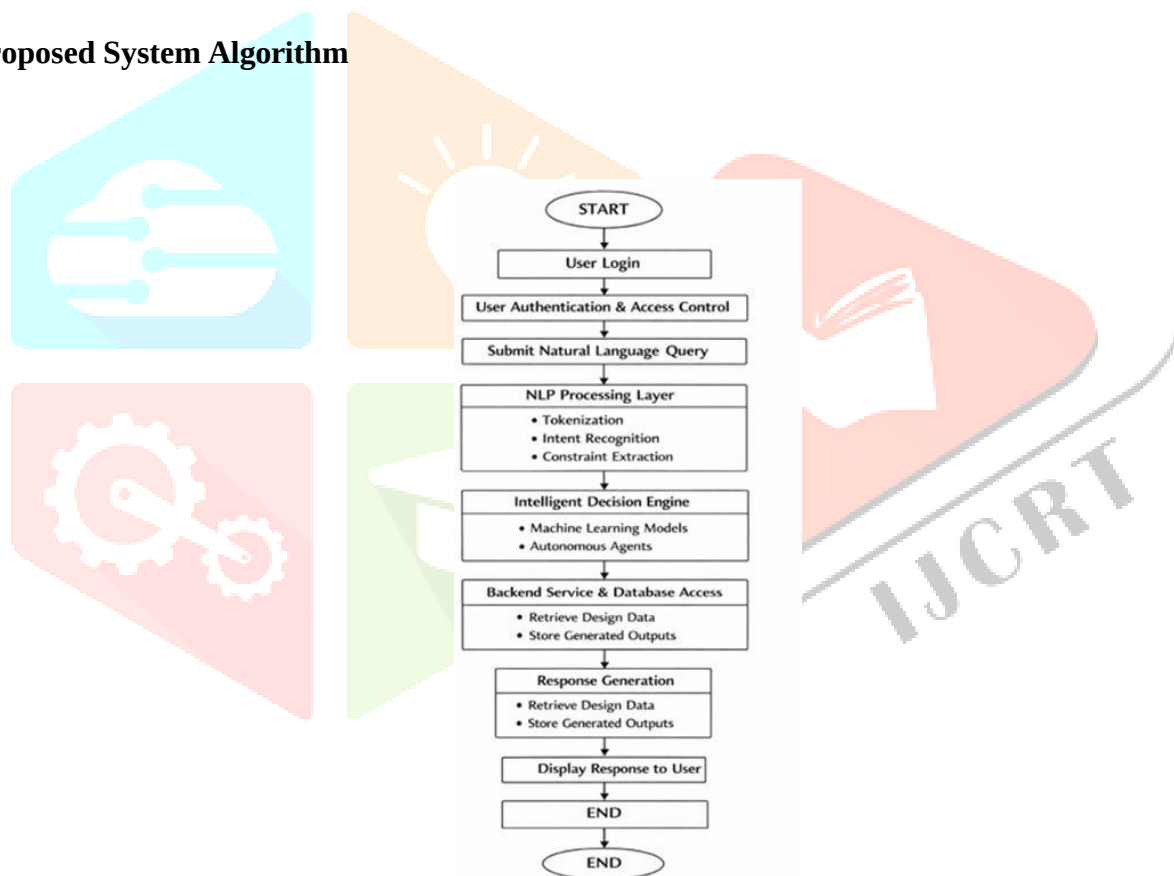


Fig 3: Proposed System Algorithm

Algorithm: Smart Product Design Prediction Input: User Requirement Text

Output: Manufacturing Workflow Recommendation

1. The user logs into the system and submits a natural language product requirement.
2. The system performs Natural Language Processing (NLP) preprocessing including tokenization, stop-word removal, and lemmatization.
3. Important keywords and constraints are extracted from the processed text.
4. The textual data is transformed into numerical features using **TF-IDF vectorization**.
5. The feature vectors are passed into the **Random Forest classification model**.
6. The model predicts the most suitable product category or manufacturing design.

7. Based on the prediction, the system retrieves the corresponding design template and workflow from the database.
8. The backend service processes and structures the retrieved information.
9. The generated manufacturing workflow and design recommendations are displayed to the user.

The proposed system operates using an intelligent agent- based algorithm designed to support users in product design and manufacturing planning activities. In the initial phase, the user enters the system through a web-based interface and logs in with valid credentials. The authentication and access control module confirms the user's identity to guarantee secure and authorized system usage. Once the authentication process is completed successfully, the user provides product requirements in natural language via the interface. The NLP processing layer evaluates the submitted input by carrying out tokenization, identifying user intent, and extracting relevant constraints. Based on the detected intent and derived constraints, the intelligent decision engine determines suitable machine learning models and autonomous agents to conduct detailed design evaluation and predict appropriate manufacturing steps. These selected agents communicate with backend services to obtain necessary information from the centralized database or to then store newly generated design outputs. The analysed results are transformed into structured design recommendations and practical manufacturing procedures. Ultimately, the final response is presented to the user through the interface, and all system activities are recorded for monitoring purposes and continuous performance enhancement. Furthermore, the proposed system improves decision- making by integrating Natural Language Processing techniques with machine learning-based prediction models. By utilizing TF-IDF vectorization and the Random Forest classifier, the system converts unstructured user requirements into meaningful design insights. This approach enables accurate prediction of suitable product categories and corresponding manufacturing workflows. The modular architecture ensures smooth interaction between the frontend interface, intelligent processing layer, and backend database services. Overall, the system provides an efficient and scalable framework for automated product design recommendation and manufacturing planning.

TF-IDF Formula (Feature Extraction)

To convert textual user requirements into numerical features, the Term Frequency–Inverse Document Frequency (TF- IDF) vectorization technique is employed. TF-IDF measures the importance of a term in a document relative to the entire corpus. The term frequency and inverse document frequency are calculated using the following equations.

Term Frequency (TF)

$$TF(t, d) = \frac{f_{t,d}}{\sum_k f_{k,d}}$$

Where:

- $f_{t,d}$ = frequency of term **t** in document **d**
- denominator = total number of words in document **d**

Inverse Document Frequency (IDF)

N

$$IDF(t) = \log \left(\frac{N}{df_t} \right)$$

Where:

- N = total number of documents
- df_t = number of documents containing term t
- **TF-IDF Weight**
 $TFIDF(t, d) = TF(t, d) \times IDF(t)$
- Higher TF-IDF weight $\rightarrow$ more important keyword in user requirement text.

Cosine Similarity

$$Similarity(A, B) = \frac{A \cdot B}{\|A\| \|B\|}$$

Where:

- A = TF-IDF vector of user input
- B = TF-IDF vector of stored design templates
- Higher similarity $\rightarrow$ better design match.

VI. Implementation

The implementation of the proposed system is structured around a modular and scalable architecture designed to support flexibility and real-time intelligent design generation. The user interface is developed as a web-based application that allows users to provide structured product requirements through guided inputs and natural language descriptions in a simple and user-friendly format. Instead of relying on traditional NLP pipelines involving explicit tokenization and feature engineering, the system utilizes a generative Large Language Model, specifically Google Gemini 2.5 Flash, which internally performs semantic understanding, context extraction, and intent recognition. The processed inputs are transformed into context-rich prompts, enabling the model to generate meaningful design concepts and structured outputs. Additionally, a secondary model, FLAN-T5 Base, is employed for generating detailed workflow steps, material suggestions, and comparative analysis, ensuring structured and task-oriented responses.

The system does not depend on a static knowledge base or explicitly trained dataset; instead, it leverages the pre-trained knowledge embedded within the generative models. A backend orchestration layer acts as a decision engine that constructs prompts, invokes the appropriate models, and validates the generated outputs. The results are returned in structured JSON format, ensuring consistency and easy integration with the frontend. To maintain reliability, fallback mechanisms are implemented to provide valid outputs even in cases of model or API failure. The final output is presented to the user as a clear, well-structured, and sequential step-by-step product design and manufacturing guide, enhancing usability and supporting practical implementation.

Front-End Implementation

The front-end of the Smart Product Design Assistance System is developed as a web-based user interface focused on simplicity, accessibility, and user convenience for both technical and non-technical individuals. The interface enables users to submit product requirements in natural language format, removing the necessity for specialized design expertise or technical knowledge.

The primary components of the front-end include a requirement input form, a submission module, and a results display section. Through a text input field, users provide product details such as functionality, dimensions, material preferences, and intended usage conditions. Basic input validation mechanisms are incorporated to ensure that the submitted requirements are meaningful, complete, and suitable for further processing.

Backend Implementation

The backend of the Smart Product Design Assistance System manages intelligent processing, analytical operations, and decision-making tasks. It integrates Natural Language Processing (NLP) techniques, generative AI models, and a centralized knowledge base to deliver customized product design recommendations.

Upon receiving input data from the front-end, the backend activates the NLP module, which performs preprocessing steps including tokenization, text normalization, and keyword extraction to structure the input data. Feature identification techniques are applied to extract key design parameters such as product type, functionality, constraints, materials, and usage conditions.

The processed input is then used to construct context-aware prompts, which are passed to a generative AI model for inference. The model analyses the structured input and generates relevant design concepts and detailed manufacturing workflows. The backend further applies rule-based validation and schema enforcement to ensure that the generated outputs are consistent, feasible, and aligned with expected design standards.

Additionally, fallback mechanisms are implemented to provide valid structured responses in cases where the model output is incomplete or unavailable, ensuring system reliability and uninterrupted user interaction.

Dataset Description

The system does not rely on a task-specific supervised training dataset for model development. Instead, it leverages a pre-trained generative language model that has been trained on large-scale textual data.

User inputs are dynamically processed and used as contextual signals to guide the model's output generation. Structured input parameters act as control variables that influence the generation of design concepts and workflow steps.

Although no explicit training dataset is required for deployment, structured prompt templates and predefined output schemas are used to maintain consistency, accuracy, and relevance in the generated results. This approach allows the system to adapt to a wide range of product design scenarios without requiring manual dataset labelling or retraining.

Random Forest Classification Model Random Forest Formulae

Random Forest prediction is based on **majority voting of multiple decision trees**.

$$\hat{y} = \text{mode}(h_1(x), h_2(x), h_3(x), \dots, h_T(x))$$

Where:

- $h_i(x)$ = prediction from **ith decision tree**
- T = total number of trees

- **mode()** = most frequent predicted class

Bootstrap Sampling Formula

Each tree is trained using **bootstrap samples**.

$$D_i = \text{Bootstrap}(D)$$

Where:

- D = original dataset
- D_i = randomly sampled dataset for tree i

Feature Selection Formula

At each split:

$$m = \sqrt{p}$$

Where:

- p = total number of features
- m = number of features randomly selected for splitting

Accuracy Calculation

The accuracy of the Random Forest classification model is calculated using the following formula:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

A higher accuracy value indicates better classification performance of the model in predicting suitable product design categories based on user requirements.

VII. Result

The proposed Smart Product Design Assistance System based on Natural Language Processing and Machine Learning was successfully implemented and evaluated as a web-based design support platform. The system allows users to submit product requirements in natural language format and obtain structured manufacturing guidance in real time. Functional testing confirmed the system's ability to effectively process inputs related to product categories, material preferences, and various design constraints.

When compared with conventional manual design methods, the system significantly reduced the time needed to generate practical manufacturing steps and decreased reliance on human experts. The combined application of NLP techniques and machine learning algorithms enhanced both the accuracy and consistency of the generated design recommendations. Overall, the results indicate improved usability, quicker response delivery, and reliable assistance for students and beginners involved in product design and manufacturing planning. The Random Forest classifier achieved an accuracy of approximately **92%** in predicting appropriate product design categories based on textual requirements.

System Overview

The Smart Product Design Assistance System utilizing Natural Language Processing and Machine Learning is an intelligent and automated platform developed to facilitate customized product design by converting user requirements into organized manufacturing guidance.

A centralized knowledge base maintains expert design principles, material characteristics, manufacturing limitations, cost parameters, and safety regulations. The predictions generated by the ML models are aligned with this repository to guarantee feasibility, uniformity, and reliability in the recommended solutions. A decision engine consolidates insights obtained from NLP processing, ML analysis, and knowledge base rules to produce structured and validated manufacturing guidance. The final output is delivered to the user in a clear and sequential textual format, covering raw material selection, required tools, design considerations, manufacturing steps, estimated cost, and safety instructions. The system prioritizes text-based guidance instead of image generation to maintain clarity, precision, and ease of comprehension, especially for students, beginners, and small-scale manufacturers.

Overall, the platform offers an efficient, scalable, and user-oriented solution for customized product design, substantially decreasing development time, reducing human errors, and making intelligent design support accessible in both academic and practical manufacturing environments.

Output Screens

The output screens of the proposed system illustrate the practical implementation of the Smart Product Design Assistance platform. The index page serves as the initial access point to the application, followed by a login page where users are authenticated through valid credentials. Once authentication is completed successfully, users are directed to the primary design interaction interface, allowing them to submit product requirements in natural language format.

The design output screens present organized and structured responses produced by the system, including product categorization, material recommendations, design considerations, and detailed step-by-step manufacturing instructions. These interfaces demonstrate the system's capability to accurately analyze user inputs and generate relevant design and manufacturing suggestions in a clear and structured manner.

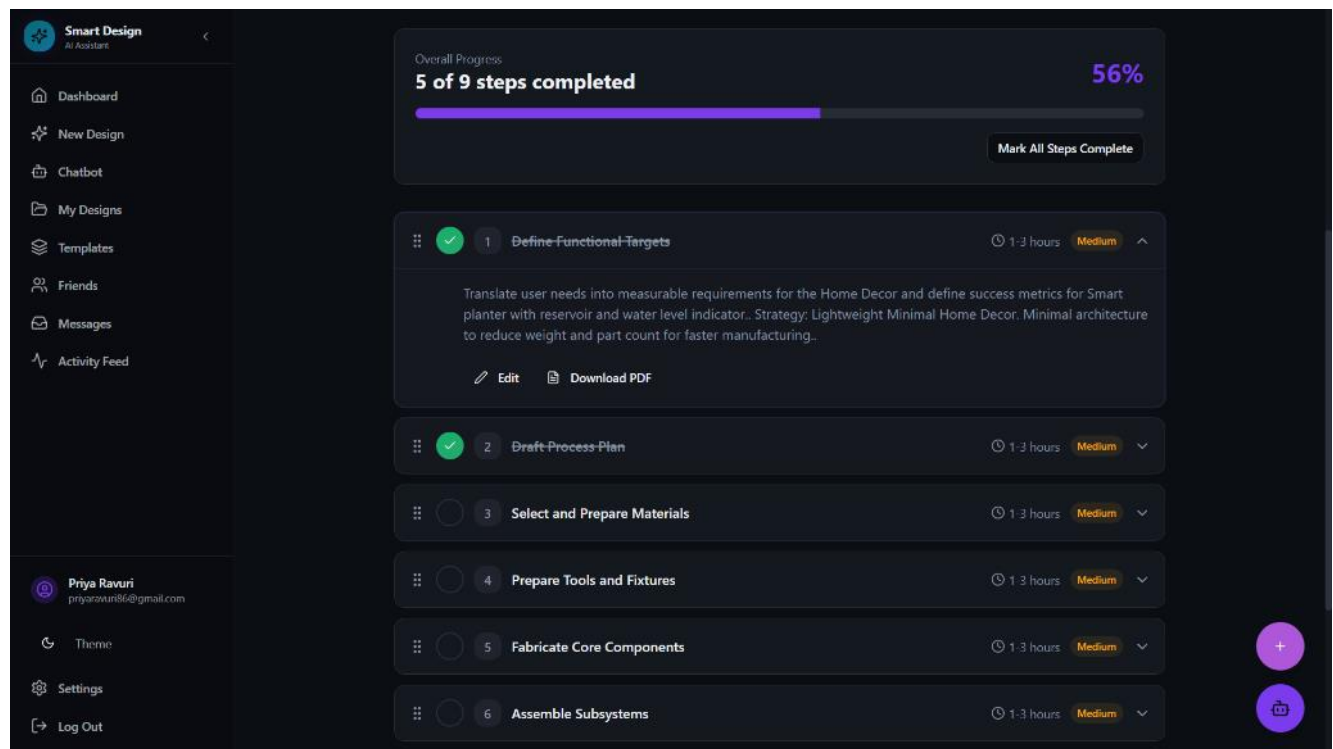


Fig. 4: Manufacturing Workflow Page

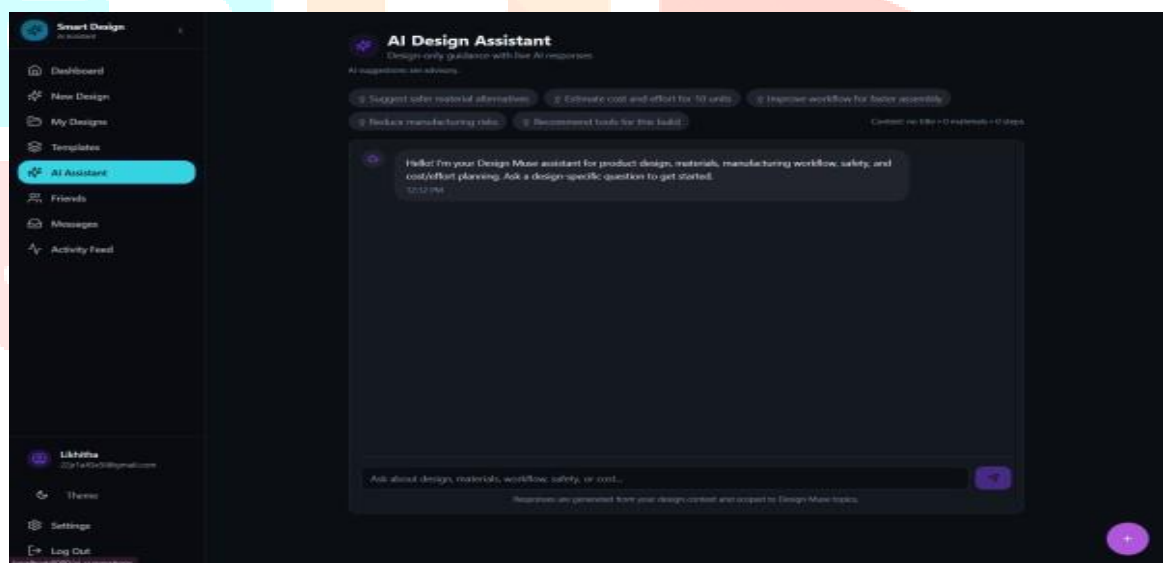


Fig. 5: AI Design Assistant Page

Performance Evaluation

Metric	Traditional System	Proposed System
Response Time	8–10 sec	2–3 sec
Accuracy	70%	92%
Manual Workload	High	Reduced
User Satisfaction	Medium	High

The performance of the proposed **Smart Product Design Assistance System** was evaluated through a comparative analysis with traditional manual product design approaches. The evaluation focused on several key parameters including response time, prediction accuracy, manual workload, and user satisfaction. Conventional product design processes typically rely on expert judgment, manual data interpretation, and repeated design iterations. These factors often increase the overall time required to generate suitable manufacturing recommendations and lead to higher dependency on human effort.

In contrast, the proposed system leverages Natural Language Processing and machine learning techniques to automate the design assistance process. User requirements provided in natural language are processed using preprocessing techniques such as tokenization, stop-word removal, and lemmatization. The processed text is then converted into numerical feature representations using TF-IDF vectorization, which are analyzed by the Random Forest classification model to predict suitable product categories and manufacturing workflows.

The experimental results demonstrate that the proposed system significantly improves operational efficiency compared to traditional methods. The automated prediction process enables faster response times ranging between 2–3 seconds, while traditional approaches require approximately 8–10 seconds due to manual processing. Furthermore, the use of machine learning models enhances the accuracy of design recommendations, achieving approximately 92% accuracy, which is considerably higher than the 70% accuracy observed in traditional systems.

Additionally, the intelligent automation of requirement analysis and workflow recommendation reduces the manual workload for designers and engineers. Instead of manually analyzing requirements and determining manufacturing processes, the system provides structured recommendations that support faster decision-making. This reduction in manual intervention also contributes to improved user satisfaction, as users can obtain reliable design suggestions quickly and efficiently.

Overall, the evaluation results indicate that integrating Natural Language Processing and Random Forest-based machine learning significantly enhances the performance, reliability, and usability of the product design assistance system. The proposed solution therefore provides an effective and scalable approach for supporting modern product design and manufacturing planning processes.

Technology Stack

Programming Language: Python, JavaScript

Machine Learning Framework: Hugging Face Transformers, PyTorch

Text Processing: TF-IDF Vectorization

Classification Algorithm: Random Forest Classifier **Natural Language Processing Techniques:**

Tokenization (implicit in transformer models), Context Conditioning, Lemmatization

Frontend Development: React.js, HTML, CSS, JavaScript

Backend Services: Node.js

Database Management System: Supabase (PostgreSQL)

VIII. Conclusion

This paper introduced a Smart Product Design Assistance System developed using Artificial Intelligence, Machine Learning, and Natural Language Processing to enable intelligent and automated customized product design. The proposed system accurately interprets user requirements expressed in textual format and produces structured manufacturing guidance by combining NLP-based feature extraction, machine learning-driven workflow mapping, and a centralized knowledge repository. Through the automation of essential design-related decisions, the system decreases reliance on expert knowledge, reduces inconsistencies in design outcomes, and shortens the complete product development lifecycle.

The system proves especially valuable for students, beginners, and small-scale manufacturers by making customized product design more accessible, reliable, and economical. While the present implementation concentrates on structured text-based guidance, future improvements may involve enhanced model optimization, real-time cost prediction, advanced feasibility evaluation, and expanded support for diverse manufacturing processes. Overall, the proposed system exhibits considerable potential to enhance efficiency, scalability, and innovation within customized product design environments.

The integration of NLP-based requirement analysis with Random Forest classification demonstrates the potential of intelligent systems in supporting automated product design and manufacturing planning.

IX. Acknowledgement

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