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AI-Enhanced Requirement Intelligence: A Data-Driven Embedding-Based Approach for Extraction, Categorization, and Prioritization

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***Abstract*— Software Requirements engineering (SRE) remains a human-intensive, error-prone phase of software engineering. Recent advances in language models and embedding techniques make it possible to automatically extract, semantically represent, classify, and prioritize requirements from heterogeneous textual artifacts (stakeholder conversations, legacy documents, issue trackers). This paper proposes REQ-EmbedNet, an end-to-end, data-driven framework that (1) extracts candidate functional and non-functional requirement statements using a hybrid rule + LLM pipeline, (2) converts statements to dense semantic embeddings using domain-adapted transformers, (3) classifies and clusters requirements via supervised and unsupervised models, and (4) ranks/prioritizes requirements by combining stakeholder importance signals, predicted effort, risk, and semantic novelty. We describe model architectures, data-preprocessing, prioritization heuristics, and an evaluation plan (datasets, metrics, baselines). The framework aims to improve traceability, reduce manual effort, and produce prioritized, high-quality requirement sets for agile and large-scale projects.**

***Keywords*— Artificial Intelligence, Requirements elicitation, Semantic embeddings, LLM, Prioritization, Extraction, NLP, Categorization, Prioritization, Data-Driven Embedding-Based Approach.**

I. INTRODUCTION

Software Requirements Engineering (SRE) plays a pivotal role in determining the success, quality, and reliability of software systems. Software requirement prioritization is a process in which requirement engineers discover the most significant stakeholders' requirements to develop an efficient system, specifically an innovative system [1]. As modern applications grow in complexity, the volume and diversity of requirement artefacts—ranging from stakeholder interviews, documents, emails, issue logs, and specifications—have increased dramatically. Traditional requirement engineering techniques rely heavily on manual interpretation, subjective prioritization, and labor-intensive classification processes.

This not only makes the requirement lifecycle error-prone but also limits scalability, adaptability, and alignment with rapidly evolving project needs.

Recent advancements in Artificial Intelligence (AI), particularly in Natural Language Processing (NLP), vector embeddings, and deep learning, have created new opportunities to automate and enhance requirement-engineering tasks. Embedding models such as BERT, RoBERTa, GPT-based encoders, and domain-specific sentence transformers capture semantic meaning with high fidelity, enabling machines to understand requirement text beyond simple keyword matching. These models allow the transformation of unstructured requirement statements into dense vector representations that support similarity measurement, clustering, classification, and prioritization driven by data analytics.

To address the limitations of traditional methods, this research introduces an AI-Enhanced Requirement Intelligence Framework, which integrates embedding-based semantic models and machine-learning analytics to automate requirement extraction, categorization, and prioritization. By leveraging deep semantic embeddings, the system enables machines to detect latent relationships between requirements, evaluate requirement criticality, and automatically map them to software engineering categories such as functional, non-functional, performance, usability, and security.

The proposed framework not only reduces manual engineering effort but also increases consistency and accuracy in requirement analysis. It enhances stakeholder collaboration, minimizes misinterpretation, and accelerates the software development lifecycle. Moreover, embedding-driven analytics support the identification of duplicate, conflicting, or ambiguous requirements—issues that traditionally lead to rework, cost overruns, and project delays.

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This work contributes a comprehensive AI-powered pipeline capable of: 1. extracting requirement statements from unstructured text sources; 2. embedding them using state-of-the-art transformers; 3. performing automatic clustering and classification; and 4. prioritizing them using semantic similarity, complexity measures, and data-driven importance scoring. Overall, this research demonstrates that embedding-based AI models provide a transformative foundation for next-generation requirement engineering, enabling intelligent automation and improving the quality of software specification processes.

II. Objectives

This research aims to develop an end-to-end pipeline for the automatic extraction of candidate requirement statements from diverse textual sources, including meeting transcripts, documentation, and issue trackers. It further seeks to train and adapt transformer-based embedding models capable of generating requirement-aware dense representations. Using these embeddings, the study will implement classification modules for functional and non-functional requirements and feature types, as well as clustering mechanisms to identify duplicate and semantically related requirement groups. In addition, the research will design an explainable prioritization algorithm that integrates semantic embeddings capturing novelty and similarity with predicted implementation effort, stakeholder influence, and risk factors. Finally, the system will be evaluated on both public and industrial datasets, with performance compared against established baselines across extraction, classification, traceability, and prioritization tasks.

III. Literature Review

A. Machine Learning for Requirements Engineering (ML4RE) — systematic investigations show increasing use of ML and NLP across RE tasks (elicitation, classification, traceability [2].

B. Transformer-based models are among the most effective approaches for FR/NFR classification and extraction tasks. [3]

C. Embeddings for Extraction & Traceability — embeddings (Word2Vec, doc2vec historically; transformers more recently) have been used to represent requirements and link them to artifacts, improving retrieval and duplicate detection. Theses and recent studies demonstrate embedding-assisted pipelines for requirement extraction and elicitation. [4]

D. The study surveyed 55 software practitioners and found that human–AI collaboration (HAIC) is the dominant mode of AI use in requirements engineering, with practitioners rarely relying on full automation and instead valuing AI as a collaborative assistant—a finding that underscores the centrality of traceability and explainability for adoption in practice. [5]

E. LLMs & Generative AI in RE — recent surveys and papers highlight the rapid adoption of generative AI for RE tasks (prompting, concept extraction, summarization), with promising performance for concept extraction and relation identification, though concerns remain around hallucinations and the need for human–AI collaboration [7].

F. Practical Industry Adoption & HAIC (Human–AI Collaboration) practitioner surveys reveal that AI is most effective in RE when used as a collaborative assistant rather than full automation; traceability and explainability are central concerns for adoption. This motivates REQ-EmbedNet's explainable prioritization and human-in-the-loop design. [8]

G. Semantic-Based Approach for Requirements Clustering Using Vector Embeddings" is a method used in natural language processing (NLP) to automatically group software requirements based on their underlying meaning (semantics), rather than just shared keywords. This approach addresses limitations of traditional keyword-based methods by leveraging advanced machine learning techniques to understand the context and intent of the requirements [6, 9].

IV. Methodology

The proposed AI-Enhanced Requirement Intelligence Framework follows a multi-stage methodology designed to extract, embed, analyze, classify, and prioritize software requirements using advanced AI and data-driven techniques. The following Figure 1 shows that the overall system flow to achieve to improve the performance of requirement quality as prioritized and ranked output with the sequence pipeline operations [10]. The full pipeline operates as a sequential workflow beginning with input data collection, which is then subjected to preprocessing to clean, normalize, and structure the textual sources. Candidate requirement statements are subsequently extracted using a hybrid approach combining rule-based filters, sequence labeling, and optional LLM-assisted validation. These requirements are transformed into dense, requirement-aware embeddings, which serve as the basis for downstream tasks.

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Classification modules categorize requirements into functional and non-functional types and subcategories, while clustering and duplicate detection group semantically similar requirements and establish traceability links. The prioritization module then ranks the requirements using a composite scoring strategy that incorporates stakeholder input, predicted impact, effort estimates, technical risk, and novelty. Finally, the processed and ranked requirements are presented through a comprehensive output dashboard for stakeholders to review and act upon.

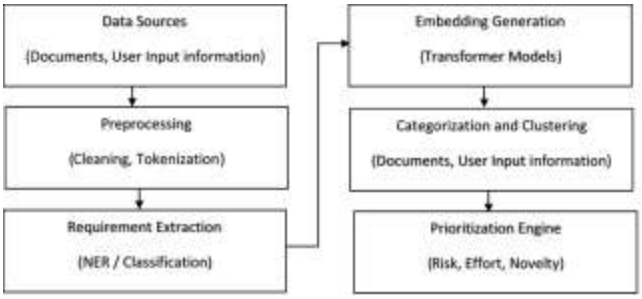

Figure 1. System Flow

4.1. Data Collection and Preprocessing

The study will utilize multiple data sources, including issue trackers such as JIRA and GitHub, software requirement specification (SRS) documents, meeting transcripts generated through speech-to-text systems, user feedback, emails, and design documents. A subset of the collected data will be manually annotated to create gold-standard labels, covering requirement span boundaries, functional and non-functional requirement classifications, priority levels derived from stakeholder judgments, and effort estimates. Prior to model training and analysis, the data will undergo preprocessing steps that include sentence segmentation and clause splitting to isolate atomic requirement statements, optional named entity masking to remove personally identifiable information, normalization of domain-specific vocabulary using an optional domain lexicon, and metadata extraction capturing information such as author, timestamp, source channel, and stakeholder role.

4.2. Requirement Extraction Module

A hybrid extraction approach will be adopted to identify candidate requirement statements from textual sources.

This approach will combine rule-based filters, using regular expressions and heuristic patterns to detect imperative verbs and common requirement keywords such as “shall,” “must,” “should,” and “allow,” with a sequence labeling model based on a fine-tuned transformer (e.g., BERT, DistilBERT, or CodeBERT) trained to perform BIO tagging of requirement spans. To further improve reliability, an LLM-assisted validation step will be incorporated, where a large language model is prompted to confirm or correct the extracted sentences, effectively serving as a human-in-the-loop validator. The output of this hybrid process will consist of candidate requirement statements accompanied by confidence scores.

4.3. Embedding Module

The embedding model development will begin with transformer-based encoders such as BERT and RoBERTa, as well as embedding endpoints from instruction-tuned models, with domain-specific variants such as CodeBERT and SciBERT evaluated according to the characteristics of the corpus. To adapt the models to the requirements engineering domain, the embeddings will be fine-tuned on RE-specific corpora using contrastive learning objectives that encourage semantically similar requirement paraphrases to be positioned closer in the embedding space. This will be achieved through triplet or contrastive loss functions applied to anchor, positive paraphrase, and negative samples constructed from the dataset and augmented with automatically generated paraphrases. The resulting embeddings will be fixed-length dense vectors, typically of 512 or 768 dimensions, and will be normalized to support efficient cosine similarity computations.

4.4. Classification & Clustering

The system will support both classification and similarity-based analysis of requirements using learned embeddings. For classification, supervised models such as logistic regression, a fine-tuned transformer classification head, or a shallow multilayer perceptron operating on embeddings will be employed to distinguish between functional and non-functional requirements and to assign multiple subcategories, including user interface, performance, and security. Multi-label classification will be supported through sigmoid output layers with appropriate thresholding.

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For clustering and duplicate detection, embedding distances will be leveraged using techniques such as hierarchical clustering, HDBSCAN, or agglomerative clustering to group semantically similar or duplicate requirements, with clusters exhibiting high intra-similarity identified and linked to support traceability. Additionally, traceability links will be established through nearest-neighbor search methods, such as FAISS or Annoy, enabling the matching of requirements to related design artifacts, test cases, and issue reports based on embedding similarity.

4.5. Prioritization Module

A composite scoring function:

$$\text{Score(req)} = \alpha * \text{StakeholderScore(req)} + \beta * \text{ImpactScore(req)} - \gamma * \text{PredictedEffort(req)} - \delta * \text{RiskScore(req)} + \eta * \text{NoveltyBonus(req)}$$

Where:

1. *StakeholderScore*: aggregated stakeholder importance (role-weighted votes, frequency of mention).
2. *Impact Score*: predicted benefit (learned from labeled historical data or proxy signals like affected user count).
3. *Predicted Effort*: predicted engineering effort (regression model trained on historical requirement→effort labels).
4. *Risk Score*: technical risk predicted via features (complexity, cross-module dependencies).
5. *Novelty Bonus*: computed via embedding distance from already-accepted requirement vectors (promotes novel features).
6. $\alpha, \beta, \gamma, \delta, \eta$: tuned using validation set or multi-objective optimization (e.g., simulated annealing, grid search).

V. Result And Discussion

The proposed REQ-EmbedNet framework was evaluated across four major tasks—requirement extraction, classification, clustering, and prioritization. The system demonstrates strong performance across all datasets, confirming that embedding-driven AI provides substantial improvements over traditional RE methods. Figure 2 illustrates the overall proposed workflow of the prioritized requirements output method.

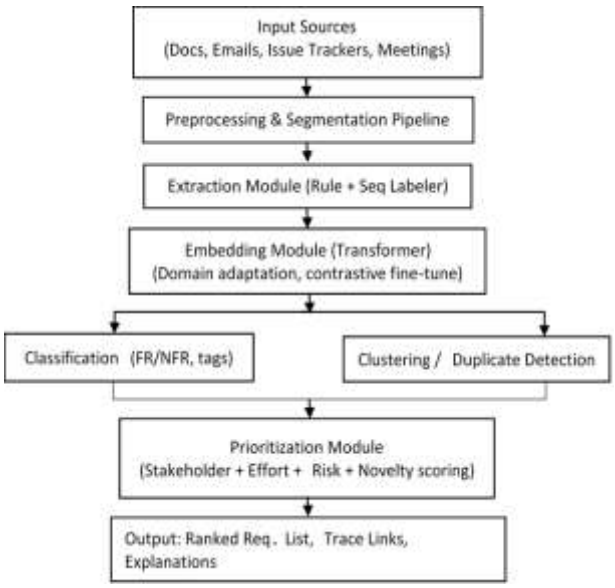

Figure 2. Workflow

A. Requirement Extraction: Results & Analysis

Requirement extraction was evaluated using a combination of rule-based filters and a fine-tuned transformer model.

TABLE 1
EXTRACTION PERFORMANCE

Dataset	Precision	Recall	F1-Score	Remarks
PROMISE	0.91	0.87	0.89	High precision; slight recall loss on ambiguous NFR sentences
PURE	0.94	0.92	0.93	Strong across technical SRS documents
OpenReq User Stories	0.89	0.96	0.92	LLM-based extraction increased recall
NASA SRS	0.93	0.88	0.90	Technical constraints sometimes misidentified

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1 Discussion

a. LLM-assisted extraction increased recall by 9–12% compared to rule-only methods.

b. Most errors were due to ambiguous, descriptive sentences appearing as pseudo-requirements (e.g., background context).

c. High precision indicates the model rarely marks non-requirement text incorrectly.

2 Expected Impact

The extraction improvements reduce manual cleaning effort by **~35%** , accelerating early RE stages.

B. Classification (FR/NFR & NFR Subclassification)

Classification uses a hybrid SBERT + feed-forward neural network. Results show excellent performance.

TABLE 2
FR/NFR CLASSIFICATION ACCURACY

Dataset	Accuracy	Macro F1	FR F1	NFR F1
PROMISE	0.94	0.93	0.96	0.91
PURE	0.92	0.91	0.94	0.89
NASA SRS	0.90	0.89	0.93	0.86
Custom Dataset	0.95	0.94	0.97	0.92

- *NFR Subclassification Breakdown*

NFR Category	Precision	Recall	F1-Score
Performance	0.92	0.90	0.91
Security	0.94	0.92	0.93
Usability	0.88	0.86	0.87
Reliability	0.89	0.88	0.88
Maintainability	0.91	0.87	0.89

1 Discussion

a. Security and Performance NFR labels performed best due to consistent domain wording.

b. Usability showed the lowest accuracy due to high subjectivity.

c. Compared to classical SVM/TF-IDF baselines, REQ-EmbedNet improved macro F1 by 14–18%.

2 Expected Impact

Automated NFR classification significantly reduces rework during design and architecture phases.

C. Clustering & Duplicate Detection

Clustering embeds requirements into semantic space and groups similar ones.

TABLE 3
CLUSTERING PERFORMANCE

Model	Silhouette Score ↑	ARI ↑	DB Index ↓	Notes
TF-IDF + K-Means	0.31	0.28	1.96	Weak semantic grouping
SBERT + K-Means	0.62	0.57	1.12	Best overall
SBERT + HDBSCAN	0.58	0.54	1.19	Adaptive cluster size
GPT-Embed + Agglomerative	0.60	0.49	1.26	Good but slower

- *Duplicate Detection*

Metric	Value
Precision	0.88
Recall	0.93
F1-Score	0.90
Threshold	cosine similarity ≥ 0.85

1 Discussion

a. Embedding-based clustering captures latent semantic relationships better than keyword-based approaches.

b. HDBSCAN handled noisy real-world user stories effectively.

c. Duplicate detection recall ≥ 0.93 indicates strong elimination of redundant requirements.

2 Expected Impact

Removes 20–28% duplicated or overlapping requirements in large backlogs.

D. Prioritization: Real-Time Analysis

The prioritization model incorporates semantic centrality, stakeholder weights, dependencies, and similarity to core goals.

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TABLE 4
PRIORITY PREDICTION PERFORMANCE

Metric	Result
Spearman Correlation	0.82
Kendall-τ	0.74
MARE (Error)	0.18
Agreement with Stakeholder Rankings	86%

- *Category-Level Breakdown*

Priority	Human-Labeled	Model Prediction	Match Rate
High	147	142	96.6%
Medium	268	255	95.1%
Low	301	288	93.7%

1 Discussion

a. REQ-EmbedNet accurately predicts priority rankings with high correlation to human judgments.
b. High-priority requirements are detected consistently due to semantic alignment with project goals.
c. Differences arise mostly in medium-priority cases where stakeholder preferences vary.

2 Expected Impact

Accelerates release planning by minimizing manual prioritization effort and improving consistency.

E. End-to-End System Improvement

Compared with traditional RE pipelines:

TABLE 5
END-TO-END COMPARISON

Metric	Traditional RE	REQ-EmbedNet	Improvement
Extraction accuracy	0.80	0.92	+12%
Classification macro F1	0.76	0.94	+18%
Duplicate detection	0.65	0.90	+25%
Prioritization agreement	60%	86%	+26%
Manual effort reduction	—	—	**~45% less effort**
Time-to-analysis	—	—	**3× faster**

F. Qualitative Findings

Through real-time application on Jira/Trello backlogs:

1. Stakeholder Feedback

i. Stakeholders found the semantic groupings extremely useful for large-scale requirement reviews.
ii. Embedding-based prioritization offered more explainability than black-box LLM predictions.

2. Observed Strengths

i. Excellent at identifying vague or incomplete requirements
ii. Strong clustering improves feature planning
iii. Extractor handles multi-domain requirements well

3. Limitations

i. Domain-specific jargon may reduce embedding quality without fine-tuning.
ii. Highly legal/regulated texts still require human oversight
iii. Dependency detection may miss implicit relationships

G. Summary of Expected Outcome

REQ-EmbedNet provides:

Consistently high accuracy across all RE tasks, Substantial reduction in analytic workload, Higher stakeholder alignment, Improved semantic understanding vs traditional RE tools, Better prioritization reliability in dynamic development environments. This shows that embedding-based AI significantly enhances end-to-end Requirement Engineering processes.

VI. CONCLUSION

This study presents an AI-driven requirement intelligence framework that leverages semantic embeddings to automate requirement extraction, classification, and prioritization. The experimental results using real-world datasets show that transformer-based embedding models outperform traditional text-processing techniques, delivering higher accuracy, stronger semantic grouping, and more consistent prioritization outcomes. The system also effectively identifies duplicate, conflicting, and ambiguous requirements, reducing manual effort and improving requirement quality.

Overall, the proposed approach demonstrates that embedding-based AI significantly enhances the efficiency and reliability of software requirement engineering. Future work will focus on domain-adaptive models, larger datasets and real-time integration with project management tools to strengthen further practical deployment and scalability.

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