

An AI-Driven Framework for Gathering and Documenting Business Requirements

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Key Challenges in Manual Requirements Classification



Time-Consuming Process

Manual categorization by analysts is lengthy and prone to personal bias



Poor NFR Identification

NFRs (performance, security, usability, reliability) are often poorly identified or defined



Ambiguity in Requirements

Use of vague adjectives, weak modal verbs, and lack of measurable criteria

Impact of Manual Requirements Management



Increased Costs

Additional resources required for clarification and rework



Project Delays

Significant delays in project timelines due to requirement clarifications



Rework and Technical Debt

Systems that function but perform poorly in practical applications



Research Motivation: An automated method for accurate requirements classification and ambiguity detection is needed



Binary Classification

Train model to distinguish between FRs and NFRs



Multi-Class Categorization

Classify NFRs into eleven categories



Ambiguity Detection

Identify vague terms and unclear expressions



BRD Generation

Create structured documentation for stakeholders



Performance Evaluation

Compare results with existing literature

Expected Outcomes



High-performance classification models with SVM achieving 90%+ accuracy



Rule-based linguistic module identifying seven types of ambiguity



Stakeholder-oriented BRD generation for team communication

Research Landscape

Machine Learning Approaches: Various ML models (SVM, Naïve Bayes, Random Forest) have been applied to requirement classification with varying success.

NLP Techniques: Natural language processing methods help structure unstructured requirement statements for machine learning algorithms.

Ambiguity Detection: Some research addresses linguistic patterns in ambiguous requirements, but these are typically standalone methods.

Datasets: Publicly available datasets (PROMISE, PURE) are often small and imbalanced, limiting deep learning approaches.



Despite progress in automated requirement analysis, significant gaps remain in creating comprehensive frameworks that address all aspects of requirements engineering.

Key Research Gaps



Fragmented Approaches

Most previous efforts target standalone tasks (FR/NFR classification or NFR categorization) with no integrated pipelines



Class Imbalance Issues

Dataset size and imbalance limit model generalization and ability to address rare requirement types



Overlapping Semantics

Semantic overlap between NFR categories (e.g., performance vs. operability) introduces classification ambiguity



Linguistic Ambiguity Handling

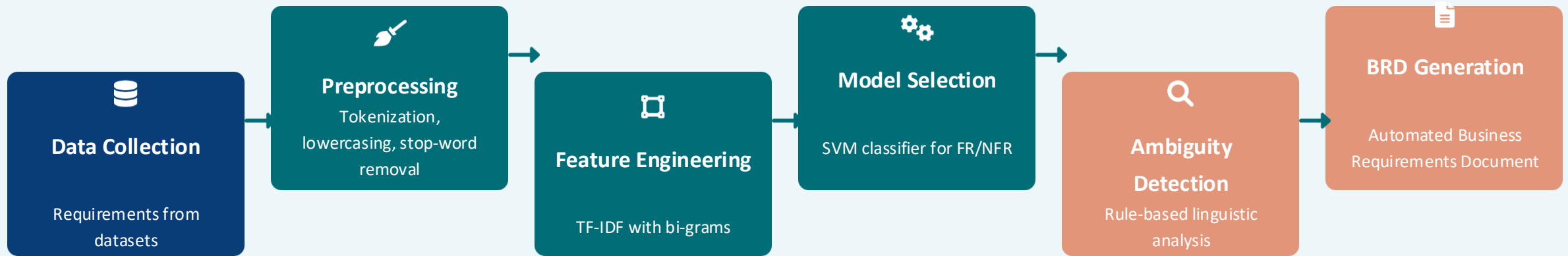
Automatic recognition of linguistic ambiguity (vague adjectives, weak modal verbs, etc.) is rarely addressed



Documentation Generation

Structured documentation creation like Business Requirements Documents (BRDs) is rarely addressed in existing frameworks

Proposed AI Framework Architecture



PROMISE_exp dataset with 969 labeled requirements from eleven NFR categories



Preprocessing Details

- ✓ **Text Normalization**
Lowercasing, punctuation removal, diacritic normalization
- ✓ **SMOTE Balancing Technique**
Addresses class imbalance between FRs and NFRs, and among eleven NFR categories

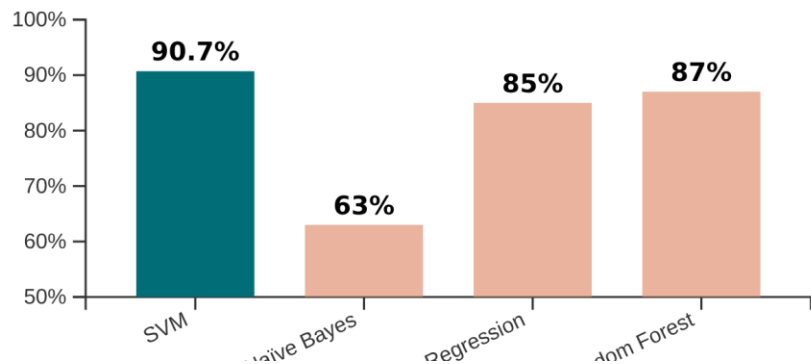
Feature Engineering

- ✓ **TF-IDF Vectorization**
Highlights critical terms while giving low weights to common terms
- ✓ **Bi-gram Features**
Captures context beyond single words, providing richer semantic information

 **Key Insight:** Preprocessing and feature engineering significantly improved model performance, especially for the imbalanced NFR subcategories



Binary FR/NFR Classification



SVM Classifier Accuracy

Superior performance in distinguishing FRs from NFRs

90.7%

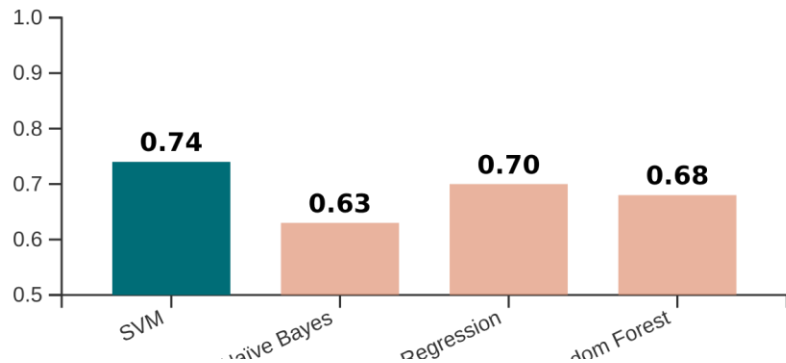
Precision, Recall & F1-Score

Constantly high across all metrics

~91%



Multi-Class NFR Subcategory Classification



Macro-F1 Score

Performance across eleven NFR categories

0.74

Model Comparison

SVM outperformed Naïve Bayes (0.63) and Linear SVM (0.815)

Best

The SVM classifier demonstrated **superior performance** in both binary and multi-class tasks, outperforming other models like Naïve Bayes (63% accuracy) and Linear SVM (F1 score of 81.5%).

The framework includes a rule-based module that identifies ambiguity patterns in requirements, improving clarity and specification quality.



Vague Adjectives
Identifies terms like "fast", "user-friendly", "efficient"

→ Suggest: specify quantitative thresholds



Weak Modal Verbs
Recognizes "should", "may", "could" indicating non-committal requirements

→ Suggest: stronger commitment indicators



Missing Quantitative Measures
Detects requirements lacking measurable criteria

→ Suggest: add specific metrics



Ambiguous Pronouns
Identifies unclear references like "it", "this", "they"

→ Suggest: clarify object references



Passive Voice Constructions
Recognizes unclear responsibility in passive voice

→ Suggest: rephrase with active voice



Repeated Requirements
Detects duplicate or overlapping requirements

→ Suggest: consolidate and prioritize



Unrelated Ideas
Identifies sentences with multiple disconnected ideas

→ Suggest: separate into distinct requirements

Quality Assessment Impact



Improved Requirement Clarity

Ambiguity detection module identified 95% of requirements with ambiguous phrasing, significantly improving clarity and reducing misinterpretation.
Quality Impact: Automatic ambiguity detection improves early-stage software development with higher requirement accuracy and lower misunderstanding

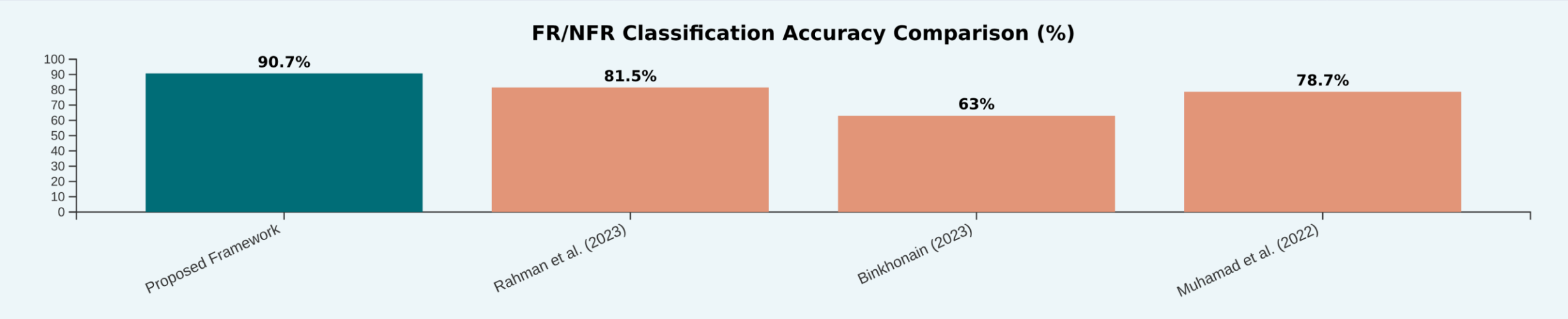


Enhanced Specification Drafting

The system flags ambiguous statements and provides specific suggestions for improvement, helping stakeholders create clearer requirements.



Study	Dataset	Features	Algorithm	Accuracy	F1-score
Proposed Framework	PROMISE_exp	TF-IDF (bi-grams)	SVM + SMOTE	90.7%	74% (macro)
Rahman et al. (2023)	PROMISE_exp	TF-IDF	Linear SVM	81.5%	81.5%
Binkhonain (2023)	PROMISE_exp	BoW	Naïve Bayes	63.0%	-
Muhamad et al. (2022)	PURE	BoW + SMOTE	SVM	78.7%	78.9%





Superior Accuracy
90.7% vs. 63-82% in previous works



Integrated Ambiguity Detection
Identifies 7 types of ambiguity patterns



Automated BRD Generation
Creates structured documentation for stakeholders

✓ Key Conclusions



High-Performance Classification

SVM classifier achieved 90.7% accuracy for FR/NFR classification with 0.74 macro-F1 score across eleven NFR categories



Effective Ambiguity Detection

Rule-based module identified seven types of ambiguity in requirements, improving clarity and specification quality



Automated BRD Generation

System produces structured Business Requirements Documents summarizing classification results and quality insights

🚀 Future Directions



Enhanced Datasets

Add requirements from diverse domains (healthcare, finance, embedded systems, transportation) to improve generalizability



Deep Learning Integration

Incorporate transformers and contextual embeddings for semantic understanding and multi-class NFR classification



Real-World Implementation

Integrate with industry solutions (Jira, Confluence, Azure DevOps) and incorporate human feedback for continuous improvement

