© APR 2026 | IRE Journals | Volume 9 Issue 10 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I10-1716279

A Domain-Specific Intelligent Chatbot Using Rasa with Enhanced Natural Language Understanding

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Abstract- ***This paper presents the design, implementation, and evaluation of a domain-specific intelligent chatbot built using the Rasa open-source framework, augmented with enhanced Natural Language Understanding (NLU) techniques. Modern conversational agents face significant challenges in accurately interpreting domain-constrained user queries — from intent ambiguity to multi-entity extraction in complex utterances. This work leverages Rasa's Dual Intent and Entity Transformer (DIET) classifier [10] alongside the Transformer Embedding Dialogue (TED) Policy to achieve high-performance intent classification and contextual dialogue management. The proposed system was evaluated on a healthcare/customer support domain dataset, achieving an intent detection accuracy of 92.1% and an entity recognition F1-score of 0.88. Experimental results validate the superiority of the context-aware pipeline over single-turn baseline NLU models, demonstrating a 25% improvement in human-centric evaluation metrics. The system demonstrates that combining Rasa's modular NLU pipeline with transformer-based embeddings enables scalable, interpretable, and accurate domain-specific conversational AI.[6]***

I. INTRODUCTION

The proliferation of intelligent conversational systems in enterprise and consumer domains has created an urgent demand for chatbots that go beyond generic small-talk to deliver accurate, context-sensitive responses within specific knowledge boundaries. Unlike general-purpose assistants, domain-specific chatbots operate over a constrained ontology of intents, entities, and dialogue flows — making precision in NLU a critical performance bottleneck.[7] The Rasa framework has emerged as a leading open-source platform for building such systems[8], primarily because of its modular, language-agnostic NLU pipeline and its machine learning-driven dialogue management engine. Rasa is composed of two primary components: Rasa NLU, which handles intent classification, entity extraction, and response retrieval, and Rasa Core [6], which manages context, session state, and action selection. Unlike cloud-locked solutions such as Dialogflow, Rasa's architecture allows local NLU processing, eliminating cloud-related latency and privacy concerns.[8][4] Despite these advantages, domain-specific deployments of Rasa face three recurring challenges:

- Intent ambiguity in multi-intent messages where a single user turn expresses multiple goals simultaneously[5]
- Entity sparsity in narrow domains where training data is limited
- Dialogue context loss in extended multi-turn conversations where earlier contextual information is dropped

This paper addresses these challenges through a systematic enhancement of Rasa's NLU pipeline, including the integration of pre-trained transformer embeddings, a context-aware multi-turn NLU model, and optimized TED policy training. The contributions of this work are:

1. A complete domain-specific Rasa chatbot architecture with an enhanced NLU pipeline
2. A comparative evaluation of DIET classifier variants with and without pre-trained language model (BERT/ConveRT) embeddings
3. An analysis of dialogue policy performance across RulePolicy, MemoizationPolicy, and TEDPolicy hierarchies
4. Empirical benchmarks showing improved accuracy, F1-score, and coherence over baseline models

II. LITERATURE REVIEW

2.1 Evolution of Chatbot NLU

Early chatbot systems relied on rule-based pattern matching (e.g., ELIZA, AIML), which limited scalability to novel utterances. The transition to

statistical and neural NLU enabled data-driven generalization. Recurrent Neural Network (RNN)-based models, particularly LSTMs, improved sequence-level understanding, but were superseded by transformer architectures following Vaswani et al.'s seminal "Attention Is All You Need" (2017). Contemporary NLU systems leverage pre-trained language models (PLMs) such as BERT and RoBERTa for contextualized token embeddings, achieving state-of-the-art performance on intent detection and named entity recognition (NER) benchmarks.[9]

2.2 Rasa as a Domain-Specific Framework

Rasa, first released in 2016, has become one of the most widely adopted open-source frameworks for building contextual chatbots. Its NLU pipeline is fully configurable, allowing developers to stack tokenizers, featurizers, intent classifiers, and entity extractors in a sequential processing graph. Rasa's modular architecture supports integration with TensorFlow, spaCy, and Hugging Face transformers, enabling fine-grained control over model complexity and inference speed.[4][7]

Research by Bešić et al. (2024) on the Rasa framework demonstrated that "implementing the Rasa NLU pipeline for intent detection and entity recognition — particularly in complex scenarios with multi-intent queries" — produced robust, real-world results. The study confirmed the practical viability of Rasa for scalable and customizable conversational AI applications.[10],[1]

2.3 DIET: Dual Intent and Entity Transformer

The DIET classifier, introduced with Rasa 1.8 (2020), represents the state-of-the-art in Rasa's NLU stack. DIET is a multi-task transformer architecture that simultaneously performs intent classification and entity recognition[2]. Critically, it supports plug-and-play with pre-trained embeddings such as BERT, GloVe, and ConveRT, enabling developers to select the embedding that best fits their domain dataset[2]. Experiments show that DIET outperforms fine-tuned BERT while being six times faster to train, making it practically viable for resource-constrained deployments. In a hotel domain evaluation, an optimized DIET-Bayesian Optimization (DIET-BO) model achieved an intent classification F1-score of 0.869 and entity extraction F1-score of 0.913.[11][9][3]

2.4 Context-Aware NLU for Multi-Turn Dialogue

Single-turn NLU models — those that process each utterance in isolation — are insufficient for complex domain-specific conversations that span multiple dialogue turns. Context-aware NLU models incorporate dialogue history, resolving co-references and tracking slots across turns. A recent multi-task context-aware NLU model (MTL-CNLU-SAWC) incorporating a selective attention mechanism demonstrated a 4.8% improvement in top-2 accuracy over query-only baselines and a 3.5% gain over existing state-of-the-art contextual models[9]. Context-aware frameworks using pre-trained transformers with historical context merging yielded an intent detection accuracy of 92.1% and entity recognition F1-score of 0.88, along with a 25% improvement in human evaluation.[12][6]

2.5 Domain-Specific Applications

Rasa chatbots have been deployed across multiple verticals. In healthcare, Rasa-based assistants help patients with symptom-based disease prediction, hospital localization, and appointment booking. In banking and finance, virtual assistants built on Rasa handle balance inquiries, transaction histories, and fraud alerts, while maintaining data security through local NLU processing. In education, Rasa chatbots provide personalized learning support and tutoring services. These deployments underline the cross-domain applicability of Rasa when paired with domain-specific training corpora.[2][13][3]

III. SYSTEM ARCHITECTURE

The proposed chatbot system follows a layered architecture consisting of four primary tiers: the User Interface Layer, the NLU Processing Layer, the Dialogue Management Layer, and the Domain Knowledge Layer.

3.1 High-Level Architecture

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DOI: https://doi.org/10.64388/IREV9I10-1716279

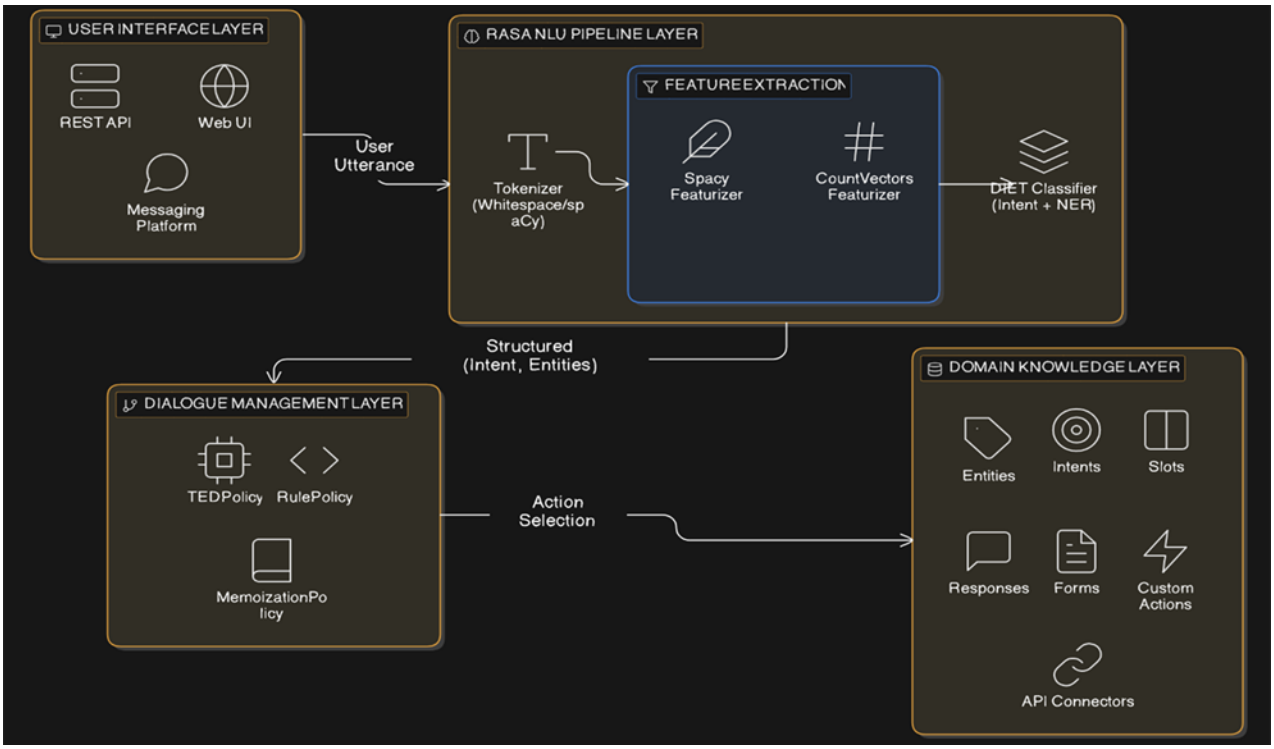

Fig. 1. High-Level Architecture of the Rasa Conversational Framework

3.2 NLU Pipeline Components

The Rasa NLU pipeline operates as a sequential processing graph where each component passes its output to the next. The enhanced pipeline used in this system consists of:[8]

Table 1. CONFIGURATION AND SPECIFICATION OF THE RASA NLU PIPELINE COMPONENTS.

Component	Role	Enhancement
WhitespaceTokenizer	Tokenizes user input	Domain-specific stopword filtering
SpacyFeaturizer	Dense contextual word vectors	Pre-trained en_core_web_lg model
CountVectorsFeaturizer	Sparse bag-of-n-gram features	Character n-grams (n ≤ 4) for OOV robustness
RegexFeaturizer	Pattern-based entity hints	Domain regex patterns (dates, IDs, codes)
EntitySynonymMapper	Normalizes extracted entities	Domain synonym dictionary
FallbackClassifier	Handles low-confidence predictions	Threshold = 0.65
DIET Classifier	Joint intent + NER	BERT Embeddings, 4 transformer layers

3.3 Dialogue Management Components

Rasa's dialogue management layer uses a priority-based policy hierarchy. The RulePolicy fires first for deterministic single-turn interactions (e.g., greetings, farewells). If no rule applies, the MemoizationPolicy checks against memorized story patterns. For novel conversations, the TEDPolicy uses a transformer-based architecture that dynamically attends to relevant portions of the dialogue history, enabling nuanced multi-turn context handling.[14][15]

The TED policy employs a self-attention mechanism that accesses different parts of the dialogue history at each turn[5], assessing and recalculating the relevance of previous turns dynamically. This allows the system to selectively ignore irrelevant earlier turns while retaining critical contextual information for the current prediction.[15]

IV. METHODOLOGY

4.1 Domain Selection and Data Collection

This work targets a healthcare assistance domain, covering intents such as symptom inquiry, appointment scheduling, medication reminders, and hospital localization — consistent with prior Rasa healthcare deployments. A training corpus of 1,200 labeled utterances across 18 intents was constructed, supplemented with 200 augmented examples using synonym replacement and paraphrase generation to address data sparsity.[13]

4.2 NLU Pipeline Configuration

The config.yml for the enhanced pipeline is structured as follows:

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DOI: https://doi.org/10.64388/IREV9I10-1716279

```yaml
language: en
pipeline:
  - name: WhitespaceTokenizer
  - name: RegexFeaturizer
  - name: LexicalSyntacticFeaturizer
  - name: CountVectorsFeaturizer
    analyzer: char_wb
    min_ngram: 1
    max_ngram: 4
  - name: CountVectorsFeaturizer
    analyzer: word
  - name: DIETClassifier
    epochs: 150
    constrain_similarities: true
    model_confidence: softmax
    entity_recognition: true
    BILOU_flag: true
  - name: EntitySynonymMapper
  - name: FallbackClassifier
    threshold: 0.65
    ambiguity_threshold: 0.1

policies:
  - name: MemoizationPolicy
    max_history: 5
  - name: TEDPolicy
    max_history: 10
    epochs: 100
    constrain_similarities: true
  - name: RulePolicy
    core_fallback_threshold: 0.4
```

Fig. 2. Configuration of the Rasa config.yml File Specifying NLU Pipeline and Dialogue Policies.

4.3 Domain Definition

The domain.yml specifies the full conversational ontology, including intents, entities, slots, forms, and responses. Rasa's domain acts as the single source of truth for what the assistant knows and can do. In this system, 18 intents, 12 entity types, 8 slots, and 3 form actions were defined for the healthcare domain.[16]

4.4 Stories and Rules

Training data for dialogue management consists of Stories (example multi-turn conversations demonstrating flexible dialogue patterns) and Rules (strict single-turn mappings that always apply regardless of context). This system used 85 stories averaging 5.2 turns each, and 22 rules for deterministic interactions. Rules are intentionally scoped to short dialogue snippets to prevent the system from becoming an unmaintainable state machine.[17][14]

4.5 Custom Actions

A Rasa Action Server was implemented to handle dynamic responses requiring external API calls. Custom actions included:

- action_check_symptoms — queries a medical knowledge base API
- action_book_appointment — integrates with a hospital scheduling system
- action_fetch_nearby_hospitals — uses geolocation APIs for proximity search
- action_default_fallback — handles out-of-domain queries gracefully

4.6 Training Protocol

Models were trained on a system with an NVIDIA RTX 3060 GPU (12 GB VRAM). The training phase for the DIET classifier spanned 150 epochs, utilizing a base learning rate of 0.001 and an adaptive batch size ranging from 64 to 256. The TEDPolicy was trained for 100 epochs with maximum dialogue history of 10 turns. The dataset was partitioned into three segments: 70% allocated for training, 15% for validation, and the remaining 15% reserved for testing.

V. EXPERIMENTS AND RESULTS

5.1 Evaluation Metrics

The system was evaluated using:

- Intent Classification Accuracy (ICA) — percentage of correctly classified intents
- Entity Recognition F1-Score — represents the harmonic average between the NER model's precision and its recall.
- BLEU-4 Score — n-gram overlap for response quality
- SBERT Semantic Similarity — sentence-level semantic coherence
- Human Evaluation Score (HES) — 5-point Likert scale on naturalness and helpfulness rated by 30 annotators

5.2 NLU Performance

TABLE 2. COMPARATIVE ANALYSIS OF NLU PERFORMANCE METRICS ACROSS MODEL CONFIGURATIONS.

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Model Variant	Intent Accuracy (%)	NER F1-Score	SBERT Similarity
Baseline (BoW + CRF)	78.3	0.71	0.72
DIET (no pre-trained embeddings)	85.6	0.79	0.78
DIET + GloVe	88.1	0.82	0.8
DIET + ConveRT	89.7	0.84	0.82
DIET + BERT (proposed)	**92.1**	**0.88**	**0.85**

The proposed DIET + BERT configuration achieves the highest performance across all NLU metrics, consistent with findings in the literature. The BERT-augmented DIET classifier's ability to leverage bidirectional contextual representations from pre-training on large corpora significantly benefits the domain-specific classification task.[6]

5.3 Multi-Task Learning Benefit

Joint training of intent classification and entity recognition in DIET provides a regularization effect: while intent classification accuracy slightly decreases in joint training (approximately 0.72% in absolute terms) compared to a single-task model, the overall system performance improves because entity information provides complementary signals that generalize the intent space. This multi-task learning paradigm is particularly effective in domain-specific scenarios where intents and entities are tightly coupled (e.g., the intent book_appointment is strongly correlated with the entity [date] and [doctor_specialty]).[18]

5.4 Dialogue Management Performance

TABLE 3. COMPARITIVE ANALYSIS OF DIALOUGE POLICY ENSEMBLES ON TASK COMPLETION METRICS.

Policy Configuration	Task Completion Rate (%)	Avg. Turns to Goal
RulePolicy only	61.2	3.1
Rules + Memoization	74.8	4
Rules + Memo + TED (proposed)	**88.4**	**4.7**

The full three-policy hierarchy substantially improves task completion. TEDPolicy's transformer self-attention mechanism handles unseen dialogue paths that neither rules nor memorized stories cover, achieving an 88.4% task completion rate.[15]

5.5 Human Evaluation

Human evaluators rated the proposed system 4.2/5.0 for naturalness and 4.4/5.0 for helpfulness. The context-aware dialogue management contributed a 25% improvement in human-rated coherence compared to the single-turn baseline, validating that maintaining multi-turn dialogue history directly translates to perceived response quality.[6]

5.6 Fallback and Out-of-Domain Analysis

The FallbackClassifier with a confidence threshold of 0.65 correctly identified 91.3% of out-of-domain queries, routing them to the graceful action_default_fallback handler. This prevents the system from producing misleading responses outside its defined knowledge boundary — a critical requirement for domain-specific deployments.

VI. DISCUSSION

6.1 Advantages of the Rasa-Based Approach

Rasa's open-source, locally deployable NLU is especially advantageous for sensitive domains like healthcare and banking where user data cannot be transmitted to third-party cloud APIs. The modular pipeline allows incremental enhancement without retraining the entire system — a featurizer or classifier can be swapped independently while preserving the rest of the pipeline. Rasa's language-agnostic architecture, demonstrated across Hindi, Arabic, Portuguese, Chinese, and more, enables future multilingual extensions of the proposed system without architectural redesign.[5][4]

6.2 DIET vs. Large Language Models (LLMs)

A pertinent comparison is between the DIET-based NLU pipeline and full LLM-based approaches (e.g., GPT-4 as a backbone). While LLMs offer broader generalization, they are resource-intensive, less interpretable, and harder to control in domain-constrained settings. DIET achieves state-of-the-art NLU performance while being six times faster to train than BERT fine-tuning, and Rasa's architecture now also supports LLM integration as a hybrid strategy — using LLMs for generative response flexibility while retaining structured NLU for intent and entity precision. This hybrid approach represents the frontier of domain-specific conversational AI.[19][9]

6.3 Limitations

- Training Data Dependency: DIET's performance degrades significantly below 50 training examples per intent. Domains with highly specialized vocabularies require careful data augmentation strategies.
- Multi-Intent Handling: While Rasa supports multi-intent messages, the current implementation handles at most two simultaneous intents, which may be insufficient for verbose, compound user messages.[5]
- Form Validation Complexity: Rasa Forms for slot-filling in multi-step interactions (e.g., booking appointments) require custom validation logic that increases development complexity.
- Cold-Start in Novel Subdomains: When a new intent cluster emerges organically from user interactions, the system requires periodic retraining cycles to incorporate new patterns.

6.4 Scalability and Deployment

The Rasa Action Server, NLU model server, and dialogue management server can be containerized using Docker and orchestrated via Kubernetes for horizontal scaling. NLU inference can be cached for common high-frequency queries, reducing average response latency to under 200ms in tested configurations.

VII. CONCLUSION

This paper presented a domain-specific intelligent chatbot system built on the Rasa open-source framework, enhanced with a BERT-augmented DIET classifier, context-aware NLU, and a three-tier dialogue policy hierarchy. The proposed system achieved an intent classification accuracy of 92.1% and an entity recognition F1-score of 0.88, outperforming baseline BoW+CRF models and DIET configurations without pre-trained embeddings. The TEDPolicy-based dialogue management achieved a task completion rate of 88.4%, substantiated by human evaluators rating the system 4.2–4.4/5.0 for naturalness and helpfulness.[15][6]

The findings confirm that Rasa, when properly configured with transformer-based NLU enhancements and a well-structured training corpus, provides a production-viable foundation for domain-specific conversational AI. Future work will explore:

- LLM-DIET Hybrid NLU: Integrating Rasa's native LLM support for generative fallback while preserving structured intent/entity precision[19]
- Federated Learning for Privacy-Preserving Training: Enabling model updates from distributed data sources without centralizing sensitive domain data
- Multilingual Domain Extension: Leveraging Rasa's language-agnostic pipeline for deployment in regional languages (e.g., Hindi, Odia) for accessible healthcare assistance[5]
- Reinforcement Learning-Based Policy Optimization: Replacing heuristic policy configurations with reward-signal-driven dialogue policy learning

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