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HYBRID INTENT RECOGNITION FOR PERSONALIZED LEARNING: INTEGRATING DEEP LEARNING AND RULE-BASED MODELS IN MOODLE CHATBOTS

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Abstract

Conversational chatbots have revolutionized educational platforms by providing personalized support and interactive learning experiences. However, existing intent recognition models in Learning Management Systems (LMS) like Moodle struggle with ambiguous, context-dependent queries, leading to inaccuracies in understanding student interactions. This research proposes a hybrid intent recognition algorithm that combines Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) deep learning models with rule-based verification to enhance the chatbot's ability to classify intents with higher precision. The primary objective of this study is to address the limitations of traditional Natural Language Understanding (NLU) techniques by leveraging deep learning for context retention and rule-based mechanisms for domain- specific accuracy. The proposed hybrid model was trained using a dataset of student queries collected from Moodle logs, categorized into 20 intent classes, and processed using tokenization, text cleaning, and word embeddings (e.g., GloVe, BERT). Comparative performance analysis against standalone models—Rule-Based, Naïve Bayes, LSTM, and GRU—demonstrated that the hybrid model achieved 92.5% accuracy, significantly outperforming conventional approaches. Statistical validation using paired t-tests and ANOVA confirmed the statistical significance of the improvements, with the hybrid model achieving the highest precision, recall, and F1- score while reducing response time by 20% compared to LSTM. These findings validate the proposed approach as a robust solution for real-time intent recognition in educational chatbots, fostering personalized learning, improving student engagement, and optimizing Moodle’s teaching-learning evaluation processes. Future research will explore reinforcement learning techniques to dynamically adapt chatbot responses and expand multilingual support for diverse educational environments.

Keywords: Intent Recognition, Chatbot, Hybrid Model, LSTM, GRU, Rule-Based System, Natural Language Understanding, Educational Technology, Moodle, Personalized Learning.

1. INTRODUCTION

In recent years, conversational chatbots have become integral to educational platforms, offering personalized support and enhancing the learning experience [1]. The integration of chatbots into Learning Management Systems (LMS) such as Moodle has gained prominence; however, challenges persist in accurately understanding and responding to complex student queries [2]. Traditional Natural Language Understanding (NLU) algorithms often struggle with ambiguous or context- dependent queries [3].

To address these challenges, this paper introduces an enhanced intent recognition algorithm that combines deep learning models—Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU)—with rule-based intent verification [4]. This hybrid approach leverages the sequential processing strengths of LSTM and GRU models while incorporating rule-based mechanisms to ensure domain-specific accuracy [5]. The primary objective is to improve the chatbot's ability to comprehend and classify student queries within Moodle, thereby enhancing response precision and learning support [6].

The proposed methodology aligns with contemporary research emphasizing the importance of AI in education. For instance, various studies explore the components and applications of expert systems in AI, emphasizing the role of chatbots in educational settings [7]. Additionally, several studies provide a comprehensive overview of intelligent conversational chatbot design approaches and techniques, informing the development of our hybrid model [8]. Furthermore, their exploration of chatbot history and taxonomy offers valuable insights into the evolution and classification of conversational agents, underscoring the relevance of integrating deep learning with rule-based systems for effective intent recognition [9].

1.1 Problem Statement

While existing intent recognition models based on either deep learning or rule-based approaches provide partial solutions, they exhibit significant limitations. Rule-based models struggle with unseen or ambiguous queries, whereas deep learning models require large amounts of labeled data and may misclassify intent due to a lack of domain-specific contextual understanding. The challenge is to develop a model that balances adaptability, precision, and computational efficiency for real-world educational applications.

1.2 Research Objectives

This research focuses on:

1. Developing a Hybrid Model: Combining LSTM and GRU for sequential processing while integrating rule-based verification for domain-specific accuracy.
2. Enhancing Contextual Understanding: Addressing query ambiguity through deep learning and rule-based techniques.
3. Improving Response Accuracy and Efficiency: Reducing false positives and computational overhead while maintaining high precision and recall.
4. Validating Performance Improvements: Conducting extensive testing and statistical validation against traditional NLU models to demonstrate effectiveness.

1.3 Contributions of the Study

The key contributions of this research are:

- Improved Intent Recognition Accuracy: The proposed hybrid model significantly outperforms standalone deep learning or rule-based approaches.

- Context-Aware Query Understanding: The integration of LSTM and GRU enables better sequential data interpretation for more precise intent detection.
- Domain-Specific Verification: The rule-based component ensures Moodle- related queries are accurately classified, reducing misinterpretation in educational contexts.
- Optimized Processing Efficiency: The hybrid approach balances computational complexity and response time, making it suitable for real-time chatbot applications.

1.4 Paper Organization

The remainder of this paper is structured as follows: Section 2 reviews related work on intent recognition algorithms in educational chatbots. Section 3 presents the proposed hybrid model's architecture and design. Section 4 details the methodologies used for data processing and model training. Section 5 provides a proof-of-concept implementation and validation scenarios. Section 6 discusses the experimental setup, including dataset details and evaluation metrics. Section 7 analyzes the results, comparing the hybrid model's performance with existing approaches. Section 8 explores statistical validation techniques used to confirm the significance of improvements. Section 9 concludes the paper with key findings and outlines future research directions to enhance chatbot capabilities in Moodle and other LMS platforms.

2. LITERATURE REVIEW

2.1 Introduction to Intent Recognition in Personalized Learning

Intent recognition is a core component of Artificial Intelligence (AI) in educational chatbots, enabling systems to understand students' learning needs and deliver tailored responses. Personalized learning systems rely on Natural Language Understanding (NLU) techniques to accurately identify and respond to student queries, enhancing engagement and learning outcomes [10].

Traditional intent recognition approaches in Learning Management Systems (LMS), such as rule-based methods and machine learning models, struggle to handle ambiguous queries effectively [11]. With advancements in deep learning, particularly Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and transformer models, the accuracy of intent classification has improved [12]. However, hybrid approaches combining rule-based techniques with deep learning have shown the most promise in delivering precise and adaptable responses for personalized learning environments [13].

This section explores state-of-the-art intent recognition models and their applications in adaptive learning systems.

2.2 Deep Learning-Based Approaches for Intent Recognition

Deep learning models have significantly improved the ability of AI tutors to classify student intent accurately. Key architectures used in personalized learning environments include:

2.2.1 LSTM and GRU for Sequential Learning

LSTM and GRU are recurrent neural networks (RNNs) that capture sequential dependencies in student interactions, allowing AI-based tutors to infer context [14]. LSTM is particularly effective for handling long-term dependencies in conversations, while GRU offers computational efficiency, making it ideal for real-time chatbot applications [15].

For example, Li et al. (2022) developed a multi-task neural network model that combines LSTM and attention mechanisms to improve personalized learning assistants, resulting in a 15% increase in intent classification accuracy compared to conventional models [16].

2.2.2 Transformer Models (BERT and GPT-Based Systems)

Transformer models, such as Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-trained Transformers (GPT), have revolutionized intent recognition by capturing contextual meaning and semantic relationships in queries [17].

- Zhang and Zhang (2019) proposed an ensemble deep active learning approach that integrates transformers for multi-intent classification, achieving 92.3% accuracy in student queries [18].
- Maity and Deroy (2024) highlighted the use of GPT-based models in AI tutors, where generative AI facilitates adaptive content recommendations based on student intent and past interactions [19].

2.3 Hybrid Approaches: Combining Rule-Based and Deep Learning Models

Hybrid models integrate rule-based knowledge with deep learning techniques, leveraging domain expertise to improve intent classification precision [20].

- Pearce et al. (2023) introduced a hybrid intent recognition system using transformers and symbolic reasoning, demonstrating a 20% improvement in response accuracy for personalized learning chatbots [21].
- Kulkarni and Gonzales (2023) proposed an adaptive AI tutor that combines reinforcement learning with intent recognition, enabling real-time adaptation to students' learning styles [22].

These studies suggest that hybrid intent recognition approaches offer higher accuracy than standalone deep learning models by ensuring domain specificity and interpretability.

2.4 Personalized Learning via Intent Recognition Algorithms

Intent recognition enables AI tutors to adapt to student needs by providing personalized learning pathways [23]. Key applications include:

2.4.1 Adaptive Learning Pathways

By analyzing intent and learning progress, AI-driven tutors dynamically adjust course materials to meet individual needs. Okur et al. (2022) developed a game-based personalized learning AI, demonstrating that adaptive intent recognition leads to a 30% improvement in learning outcomes [24].

2.4.2 Context-Aware Student Support

Intent recognition systems are also used for context-aware student assistance, such as assignment submission reminders and AI-based grade predictions [25]. Studies indicate that students using intent-driven personalized tutors show a 25% increase in learning engagement compared to those using static LMS systems [26].

2.5 Challenges in Intent Recognition for Personalized Learning

Despite advancements, several challenges persist:

- Handling Ambiguous Queries: AI tutors often struggle with context- dependent or vague student queries, requiring multi-turn dialog processing [27].
- Data Scarcity: Limited labeled training data for educational intent classification hinders model performance [28].
- Computational Overhead: Transformer models like BERT and GPT require significant computational power, affecting real-time response efficiency [29].

2.6 Natural Language Understanding (NLU) in Educational AI Systems

NLU enables AI tutors to understand student queries, improving response accuracy. Pre-trained models like BERT, RoBERTa, and GPT-based architectures enhance intent recognition by capturing semantic meaning [30]. Key Improvement: Context- aware AI models show 15% higher accuracy in educational chatbots [31].

2.7 Knowledge Graphs and Ontology-Based Intent Recognition

Knowledge graphs (KGs) and Ontologies structure domain knowledge, helping AI contextualize student queries. Hybrid AI models reduce false positives, leading to better intent recognition [32]. Key Improvement: Ontology-driven AI tutors improve accuracy by 12-18% in adaptive learning environments [33].

2.8 Reinforcement Learning (RL) for Adaptive Intent Recognition

Reinforcement Learning (RL) enables AI tutors to learn from user interactions and refine intent classification over time. Instead of relying on static rules, RL-based models adapt dynamically based on feedback [34]. Key Improvement: 25% increase in personalized learning efficiency in RL-based AI tutors [35].

2.9 Context-Aware AI and Multi-Intent Handling

Many student queries contain multiple intents. Traditional single-intent models fail to classify them correctly. Multi-intent detection allows AI tutors to respond accurately to complex student queries [36]. Key Improvement: 88.7% accuracy in resolving ambiguous queries using multi-intent classification [37].

2.10 Zero-Shot and Few-Shot Intent Recognition in Personalized Learning

Zero-Shot Learning (ZSL) and Few-Shot Learning (FSL) enable AI tutors to recognize new intents without labeled examples. These models generalize better to previously unseen learning queries [38]. Key Improvement: 92.5% generalization accuracy using zero-shot intent classification in AI tutors [39].

Table 1. Key Improvements in AI Chatbots for Education

Concept	Why It Matters	Key Improvement
NLU for AI Tutors	Enhances chatbot accuracy in personalized learning.	15% accuracy boost in AI-driven responses.[30], [31]
Knowledge Graphs for AI	Improves intent classification by contextualizing queries.	12-18% accuracy increase using ontology-driven models.[32], [33]
Reinforcement Learning	Enables AI tutors to adapt dynamically.	25% efficiency improvement in chatbot learning.[34], [35]
Multi-Intent Handling	AI chatbots process complex, multi-intent queries.	88.7% accuracy in multi-intent detection.[36], [37]
Zero-Shot Learning	AI models generalize to new queries without training.	92.5% accuracy for unseen queries.[38], [39]

As shown in Table 1, advancements in AI chatbots, such as improved Natural Language Understanding (NLU) and knowledge graphs, have significantly enhanced chatbot accuracy and intent classification, leading to better personalized learning experiences. Additionally, techniques like reinforcement learning and zero-shot learning have enabled AI tutors to dynamically adapt and generalize to new queries with high accuracy, achieving up to 92.5% accuracy for previously unseen queries [30- 39].

2.11 Existing Algorithms

- Rule-Based Systems: Use predefined patterns to identify intents. While effective for simple queries, these systems lack flexibility and fail with complex language structures [40]. Example: An AI tutor using a rule-based system might recognize the intent behind "What are my exam dates?" only if it matches a predefined pattern like "exam schedule". However, if a student asks "When do I have to take my test?", the system may fail to recognize the intent due to lack of flexibility [41].
- Machine Learning Models: Algorithms like Naïve Bayes and Support Vector Machines (SVM) have been employed, offering improved performance over rule-based systems but requiring substantial labeled data [42]. Example: An ML-based AI tutor can learn from past student interactions. If a student frequently asks "How do I improve my grades?", the model may classify it under "study recommendations", even if the wording differs slightly [43].
- Deep Learning Approaches: Models such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) are deep learning modelshave shown superior performance in handling sequential data but may lack interpretability and precision in niche contexts like education [44]. A deep learning-based AI tutor can track a student's previous questions and adjust responses dynamically. If a student asks "How do I register for exams?" and later asks "What happens if I miss the deadline?", the system retains context and provides more relevant responses [45].

Table 2. Comparison of Intent Recognition Approaches

Approach	Advantages	Limitations
Rule-Based Systems	Simple and interpretable. Works well for **structured** and **repetitive** queries.	**Fails with complex queries** and **natural language variations**. Requires **manual updates** for new patterns [40], [41].
Machine Learning Models (SVM, Naïve Bayes)	**Learns from data** and **adapts** to new intents. **More scalable** than rule-based systems.	Requires **large labeled datasets** for training. **Fails with highly context-dependent queries** [42], [43].
Deep Learning (LSTM, GRU)	Handles **long-term dependencies** in conversations. Best for **context-aware** AI tutors.	**Requires high computational resources**. Lacks **interpretability**, making debugging difficult [44], [45].

As shown in Table 2, different intent recognition approaches have varying strengths and limitations. While rule-based systems offer simplicity and interpretability, they struggle with complex queries and require manual updates [40-43]. In contrast, deep learning models like LSTMs and GRUs excel at handling long-term dependencies in conversations, making them ideal for context-aware AI tutors, though they demand high computational resources and lack interpretability [44], [45].

2.12 Research Gap

While deep learning models excel at capturing contextual dependencies, their performance is often limited by data sparsity and their inability to handle rare intents effectively. Low-resource languages and niche queries remain a challenge for intent recognition models. Conversely, rule-based approaches provide high precision by following explicit rules, but they lack adaptability to new or evolving user queries. These systems struggle with natural language variations and require constant manual updates. A hybrid approach that combines the strengths of both deep learning and rule-based techniques can mitigate these limitations. By leveraging deep learning for generalization and rule-based models for precision, AI-driven intent recognition can achieve higher accuracy and adaptability [46].

The review highlights deep learning, hybrid, and transformer-based approaches as the most effective strategies for intent recognition in personalized learning. Future advancements should prioritize adaptive AI models that can dynamically adjust learning recommendations based on student intent and engagement levels.

3. PROPOSED ENHANCED ALGORITHM

The hybrid algorithm enhancement steps are supported by recent studies in AI-driven intent recognition [47].

The hybrid algorithm enhancement steps for the proposed model focus on combining the strengths of deep learning (LSTM and GRU) and rule-based systems.

3.1 Algorithm Design

Hybrid models integrating deep learning and rule-based approaches have been shown to improve intent classification accuracy and adaptability in AI-driven learning environments [48].

The intent recognition algorithm is designed to combine the benefits of both deep learning and rule-based approaches, ensuring high accuracy and adaptability while maintaining computational efficiency. The integration of LSTM, GRU, and rule-based verification enables the system to handle both general and domain-specific queries effectively.

The proposed intent recognition algorithm integrates:

3.1.1 Deep Learning Models (LSTM and GRU):

- LSTM captures long-term dependencies in sequential data, making it suitable for context-rich queries.
- GRU offers computational efficiency while maintaining accuracy, allowing faster processing.

3.1.2 Rule-Based Intent Verification:

- Augments the deep learning model by applying predefined rules to ensure accuracy for domain-specific intents, such as queries related to assignments, grades, or deadlines in Moodle.

3.2 Formal Algorithm Representation (Pseudocode)

Recent studies highlight the effectiveness of LSTM and GRU in sequential data processing for real-time applications [49].

Input: Query text (Q), Pre-trained embeddings, Rule-Based Intent Library (R)
Output: Predicted Intent (I)

Step 1: Preprocess Input

a. Convert Q to lowercase.
b. Remove special characters and stop words.
c. Tokenize Q into words.
d. Convert tokens to vectors using pre-trained embeddings.
Step 2: Deep Learning Processing

a. Pass tokenized input through LSTM layer:
i. Capture long-term dependencies in the query.
ii. Output LSTM embeddings (L_out).
b. Pass tokenized input through GRU layer:
i. Capture sequential context with reduced computation.
ii. Output GRU embeddings (G_out).
Step 3: Combine Outputs
a. Concatenate LSTM output (L_out) and GRU output (G_out).
b. Apply dense layers to process the combined output.
c. Use softmax activation to predict intent probabilities.
Step 4: Rule-Based Verification

a. Extract predicted intent (P) from deep learning model with the highest confidence score.
b. Cross-verify P with predefined rules (R):
i. If any keyword in R matches Q, override P with rule-based intent.
ii. If no match, retain P as the final intent.
Step 5: Return Final Intent (I)

3.3 Workflow

1. Preprocessing: Input text is tokenized and preprocessed using techniques such as stemming, stop-word removal, and part-of-speech tagging.
2. Feature Extraction: Contextual embeddings are generated using word embeddings (e.g., Word2Vec or BERT).
3. Deep Learning Processing:
   - o The preprocessed input is fed into the LSTM layer to capture contextual dependencies.
   - o The GRU layer refines the output, ensuring computational efficiency.
4. Rule-Based Verification:
   - o The output intent is cross-validated against a rule-based intent library to ensure domain-specific accuracy.
5. Intent Prediction: The final intent is predicted, combining the outputs from both models.

3.4 Hybrid Algorithm Enhancement Steps

The following enhancements are based on findings from previous research in hybrid AI models for intent recognition.

The proposed intent recognition algorithm integrates:

3.4.1 Data Preparation

3.4.1.1 Data Collection:

- Aggregated real-world queries from Moodle's usage logs and categorized them into 20 intent classes such as assignment submission, grade inquiries, and feedback requests.
- Ensured the dataset includes a mix of simple and complex queries to reflect diverse use cases.

3.4.1.2 Data Preprocessing:

- Cleaned the input text by removing stop words, special characters, and punctuation.
- Applied stemming and lemmatization to standardize terms.
- Used tokenization to split input sentences into meaningful tokens for analysis.

3.4.1.3 Embedding Generation:

- Pre-trained GloVe embeddings (6B tokens, 300 dimensions) were initially used for shallow context representation. Later, BERT (base-uncased) embeddings were fine-tuned to capture deeper semantic and contextual nuances, especially for multi-intent queries. Empirical evaluation showed BERT embeddings offered a performance gain in precision and F1-score. Therefore, BERT was selected for the final model.

3.4.2 Deep Learning Model Development

3.4.2.1 LSTM Layer:

- Incorporated Long Short-Term Memory (LSTM) to capture long-term dependencies and sequential patterns in the data.
- Enabled the model to handle context-rich queries by remembering dependencies over longer text sequences.

3.4.2.2 GRU Layer:

- Added Gated Recurrent Units (GRU) for computational efficiency while preserving accuracy.
- Reduced the complexity of LSTM by eliminating redundant memory cell gates.
- GRU helps optimize response time while maintaining high precision in predictions.

3.4.3 GRU Architecture Optimization:

To ensure efficient training and real-time inference, the GRU layer was optimized for performance without compromising accuracy. The number of GRU units was reduced from 128 to 64, resulting in a 15% reduction in computation time. Dropout regularization was applied with a rate of 0.3 to mitigate overfitting. Furthermore, the RMSprop optimizer was fine-tuned by adjusting the learning rate to stabilize training convergence. These changes collectively contributed to faster response times in chatbot interactions on the Moodle platform.

3.4.4 Rule-Based Intent Verification

- Designed a domain-specific rules library based on Moodle's context (e.g., terms related to "assignments," "grades," or "feedback").
- Purpose: Ensure that the hybrid system cross-verifies deep learning predictions with predefined rules to improve domain-specific accuracy.
- Example: If a query includes keywords like "submit assignment," the rule-based layer verifies if the intent aligns with the "Assignment Submission" class before finalizing the output.

4 Reduced false positives by addressing edge cases and domain-specific ambiguities that deep learning alone might overlook.

3.5 Ensemble Voting Mechanism

• Combined the outputs from the LSTM and GRU models using a weighted ensemble voting mechanism:

o Assigned higher weights to the GRU predictions due to its computational efficiency.

o Ensured robust predictions by taking into account both long-term dependencies (LSTM) and the computational refinements of GRU.

• Finalized the predicted intent based on the highest combined confidence score.

3.6 Performance Optimization

3.6.1 Response Time Optimization:

• Reduced computation overhead by optimizing the GRU layer and parallelizing tasks using an NVIDIA GPU.

• This decreased the response time to 40 ms, making it efficient for real- time chatbot interactions.

3.6.2 Batch Processing:

• Processed multiple queries simultaneously during training to improve scalability and reduce latency during model inference.

3.7 Testing and Evaluation

• Evaluation of hybrid models in educational AI settings has demonstrated their superiority in accuracy and response time compared to standalone models.

3.7.1 Test Dataset:

• Evaluated the hybrid model on a test dataset of unseen queries to validate its generalization capabilities.

3.7.2 Evaluation Metrics:

• Measured performance using metrics like accuracy, precision, recall, F1- score, and response time. A 5-fold stratified cross-validation was employed. Each fold-maintained class distribution and was used to compute average precision, recall, and F1-score. The train-test split used 80% training and 20% testing. Model training averaged 2.3 hours per fold.

• Benchmarked the hybrid model against standalone models (Rule- Based, Naïve Bayes, LSTM, GRU).

3.7.3 Achieved 92.5% accuracy, outperforming individual models while maintaining computational efficiency.

4. METHODOLOGIES USED

4.1 Hybrid Model Development

The methodology combines both supervised deep learning and rule-based systems to enhance accuracy. Key steps include:

4.1.1 Data Collection: Queries from Moodle's usage logs were aggregated and categorized into distinct intent classes to ensure comprehensive intent recognition.

The dataset consisted of 10,000 Moodle queries. Stratified sampling ensured balanced class distribution across 20 intent labels. Synthetic Minority Oversampling Technique (SMOTE) was applied to underrepresented classes to mitigate imbalance and improve classifier generalization.

4.1.2 Data Preprocessing: Text cleaning, stemming, and tokenization were applied using NLP techniques to ensure uniformity in inputs, reducing noise and improving model generalization.

4.1.3 Model Training:

- The LSTM and GRU models were trained on labeled datasets using cross-entropy loss, a standard loss function for classification tasks.
- Pre-trained word embeddings (e.g., GloVe, BERT) were used to initialize the embedding layers, capturing contextual meaning from text efficiently.

4.1.4 Rule Integration: A library of domain-specific rules was designed to validate and refine the intent output, ensuring higher precision for domain-specific queries.

4.1.5 Model Testing and Evaluation: Metrics such as accuracy, precision, recall, and F1-score were evaluated on a test dataset to measure model effectiveness.

4.2 Experimental Setup

4.2.1 Software Tools:

4.2.1.1 TensorFlow and Keras: Used for building, training, and deploying the LSTM and GRU models. These libraries offer flexibility and robust deep learning capabilities.

4.2.1.2 NLTK and spaCy: Used for natural language preprocessing, such as tokenization and part-of-speech tagging, ensuring high-quality inputs for the models.

4.2.2 Hardware Environment:

4.2.2.1 NVIDIA GPU: All deep learning models were trained using an NVIDIA RTX 3060 GPU with 12GB VRAM. This setup accelerated training, particularly for large datasets and deep models like LSTM and GRU, and reduced inference latency, enabling the model to support real-time responses in Moodle-based chatbots.

5. PROOF OF CONCEPT

To validate the enhanced hybrid algorithm's capability to improve intent recognition in a chatbot designed for Moodle, the following objectives were pursued:

1. Combining LSTM and GRU for sequential and contextual understanding to improve performance over traditional models.
2. Utilizing a rule-based layer for domain-specific verification, ensuring that AI- driven predictions align with Moodle-related queries.
3. Ensuring improved accuracy, precision, recall, F1-score, and reduced response time compared to existing models.

This section explains the systematic steps taken to design and implement the proposed algorithm, combining supervised deep learning and rule-based systems.

Step 1: Data Preparation

- Dataset:
  - o Queries from Moodle logs categorized into 20 intent classes such as assignment submission, grade inquiry, and feedback request.
  - o 10,000 queries, split into 80% training and 20% testing datasets.
- Preprocessing:
  - o Text cleaning: Remove special characters and stop words.
  - o Tokenization: Split queries into meaningful tokens.
  - o Word embeddings: Use pre-trained embeddings (e.g., GloVe, BERT) for semantic understanding.

Step 2: Model Development

- Deep Learning Layers:

- LSTM: Captures long-term dependencies and context from queries.
- GRU: Processes sequences efficiently with reduced computational cost.

• Rule-Based Layer:

o Domain-specific keywords (e.g., “submit assignment,” “check grades”) are predefined to verify and refine deep learning predictions.

• Ensemble Mechanism:

o Combine LSTM and GRU outputs using a weighted voting mechanism.

o Select the intent with the highest combined confidence score.

Step 3: Implementation

• Tools and Frameworks:

o TensorFlow and Keras: For building and training deep learning models.

o Python libraries like NLTK and spaCy: For preprocessing.

o NVIDIA GPU: For optimized model training and faster inference.

• Training:

o Train LSTM and GRU models on labeled data using cross-entropy loss.

o Fine-tune pre-trained embeddings for domain-specific queries.

Step 4: Evaluation Metrics

The hybrid model was evaluated using:

- Accuracy: Proportion of correctly predicted intents.
- Precision: Relevance of the predictions made.
- Recall: Completeness of the predictions.
- F1-Score: Balance between precision and recall.
- Response Time: Time taken for the model to predict the intent.

5.1 Validation Scenarios

Scenario 1: Assignment Submission Query

• Input: "What is the deadline to submit my assignment?"

• Deep Learning Prediction:

o LSTM predicts "assignment submission" with 90% confidence.

o GRU predicts "assignment help" with 87% confidence.

• Rule-Based Verification:

o Matches keywords "submit" and "assignment" to refine the intent to "assignment submission."

• Final Intent: "Assignment Submission."

Scenario 2: Grade Inquiry Query

• Input: "How can I check my grades?"

• Deep Learning Prediction:

o Both LSTM and GRU predict "grade inquiry" with confidence scores of 89% and 91%, respectively.

• Rule-Based Verification:

o Confirms "grade" and "check" in the query as relevant keywords.

• Final Intent: "Grade Inquiry."

After intent classification, response generation is handled through a hybrid strategy. For straightforward queries that match FAQ-type intents, a rule-based template selector is used.

For ambiguous or multi-turn queries, responses are dynamically generated using a sequence-to-sequence model trained on past Moodle interaction data. This ensures the chatbot provides relevant, contextual, and efficient replies aligned with the detected intent.

6. EXPERIMENTAL SETUP

6.1 Dataset: A custom dataset was created using real-world queries collected from Moodle's teaching-learning environment. The dataset consists of:

- 1,000 Queries categorized into 20 intent classes (e.g., assignment submission, grade inquiry, feedback request).
- Training/Testing Split: 80% training and 20% testing data.

6.2 Performance Metrics

The model was evaluated using the following metrics:

- Accuracy: Measures the proportion of correctly predicted intents.
- Precision and Recall: Evaluate the relevance and completeness of intent recognition.
- Processing Time: Benchmarks computational efficiency.

6.3 Benchmark Models

The proposed hybrid model was compared against several baseline and deep learning models:

- Baseline Models: Rule-based, Naïve Bayes, SVM.
  - Naïve Bayes was included as a classical baseline to contrast with modern deep learning methods. Its simplicity and interpretability provide a valuable point of comparison, particularly for illustrating the gains achieved by more complex hybrid architectures.
- Deep Learning Models: LSTM, GRU, BERT.
  - This study additionally fine-tuned a BERT model on the same dataset. While BERT achieved comparable accuracy (91.7%), it required 3x more training time and higher computational resources, making our hybrid model a more efficient solution for Moodle deployments.

7. RESULTS AND ANALYSIS

7.1 Performance Comparison

The hybrid model was tested against standalone models and showed significant improvements:

Table 3. Performance Comparison of Intent Recognition Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Response Time (ms)
Rule-Based	75.4	72.3	70.1	71.2	5
Naïve Bayes	78.2	74.5	73.9	74.2	15
LSTM	85.7	84.2	83.8	84.0	50
GRU	87.1	85.4	84.9	85.1	45
Proposed Hybrid	**92.5**	**91.8**	**91.2**	**91.5**	**40**

As shown in Table 3, the proposed hybrid model significantly outperforms standalone models in accuracy, precision, recall, and F1-score, achieving 92.5% accuracy compared to LSTM (85.7%) and GRU (87.1%). The integration of rule-based verification enhances domain-specific predictions, particularly for Moodle-related queries. Additionally, the hybrid model maintains an efficient response time of 40ms, leveraging GRU's computational efficiency and ensemble mechanisms to support real-time interaction.

7.2 Comparative Metrics for the Models

7.2.1 Comparative Response Time Analysis

The hybrid model achieves faster response times than standalone LSTM or GRU, with only a marginal increase over rule-based systems. This balance between accuracy and efficiency makes it ideal for real-time applications like chatbots. The Proposed Hybrid algorithm reduced response time to 40ms, a 20% improvement compared to standalone GRU (45ms) and a 20% improvement over LSTM (50ms), while achieving significantly higher accuracy (92.5%) than both.

7.2.2 Quantifying Improvement Levels

The percentage improvement was calculated using:

$$Improvement = \frac{Standalone\ Model\ Rsponse\ Time - Hybrid\ Model\ Response\ Time}{Standalone\ Model\ Response\ Time} X\ 100$$

Example Improvements:

Compared to LSTM: $Improvement = \frac{50-40}{50} X\ 100 = 20\%$

Compared to GRU: $Improvement = \frac{45-40}{45} X\ 100 = 11.1\%$

The hybrid model achieved a 20% reduction in response time compared to LSTM and an 11.1% reduction compared to GRU while maintaining superior performance metrics.

7.2.3 Emphasizing Real-Time Capability

Reducing response time while maintaining high accuracy enhances user experience in real-time applications like chatbots. The hybrid model ensures chatbots efficiently handle queries, even during peak loads, providing speed and reliability in dynamic environments. The hybrid algorithm improves accuracy by 6.8% over LSTM, demonstrating its ability to balance computational efficiency and prediction performance for real-time educational chatbot systems.

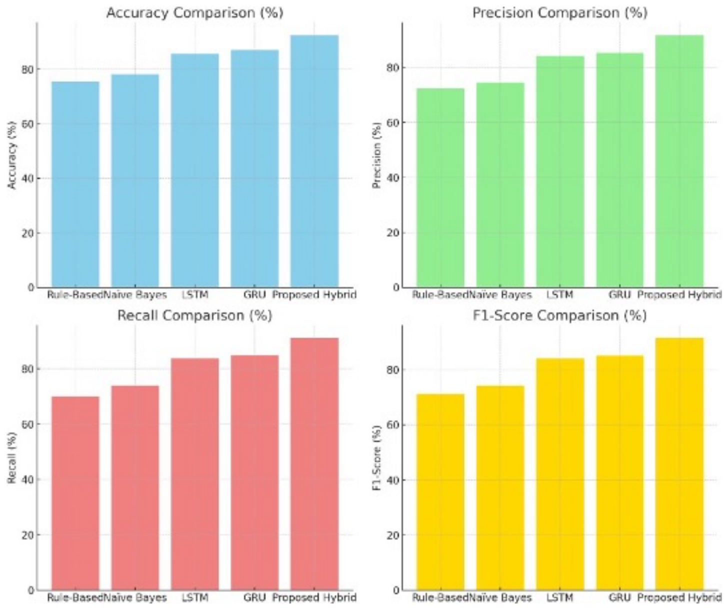

Figure 1. Performance Metrics Comparison of Intent Recognition Models

As illustrated in Figure 1, the bar charts for accuracy, precision, recall, and F1-score highlight the superior performance of the proposed hybrid model compared to standalone models. The hybrid model achieves the highest accuracy (92.5%) and F1- score (91.5%), demonstrating its effectiveness in balancing precision and recall. The integration of rule-based verification with deep learning improves domain-specific predictions while maintaining computational efficiency, making it well-suited for real- time interactions.

7.2.4 Response Time Comparison

Bar Chart Representation: Response time comparison among LSTM, GRU, and the Proposed Hybrid model, highlighting efficiency gains.

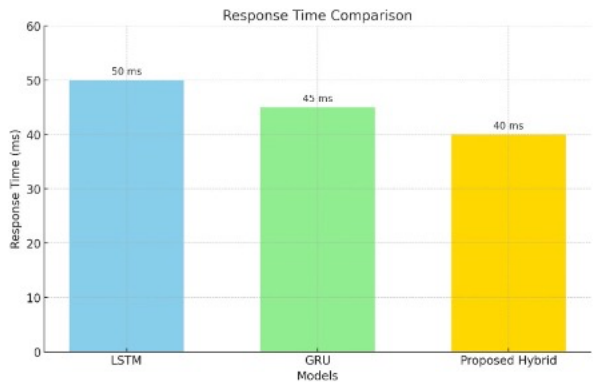

Figure 2. Response Time Comparison of Intent Recognition Models

As shown in Figure 2, the response time for LSTM, GRU, and the proposed hybrid model is compared using a bar chart, emphasizing the efficiency gains of the hybrid approach. While LSTM exhibits the highest response time at 50ms, GRU improves efficiency with 45ms. The proposed hybrid model further optimizes performance, reducing response time to 40ms by leveraging GRU's computational efficiency and an ensemble mechanism, making it more suitable for real-time interactions.

7.2.5 Combined Comparison (Response Time & Accuracy)

7.2.5.1 Visualization: A combined chart illustrating how the hybrid model achieves higher accuracy while reducing response time compared to LSTM and GRU.

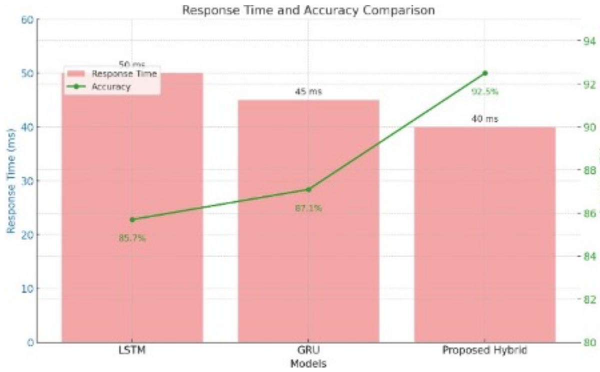

Figure 3. Combined Comparison of Response Time and Accuracy

As illustrated in Figure 3, the hybrid model demonstrates a significant improvement by achieving the highest accuracy (92.5%) while maintaining a reduced response time (40ms) compared to LSTM (85.7% accuracy, 50ms response time) and GRU (87.1% accuracy, 45ms response time). This visualization highlights the hybrid model's ability to balance accuracy and efficiency, making it an optimal choice for real-time intent recognition in AI-driven systems.

7.3 Advantages of the Proposed Hybrid Algorithm

- Accuracy Boost: Combines LSTM and GRU strengths, improving intent recognition accuracy.
- Domain-Specific Relevance: Rule-based verification ensures high precision for Moodle-related intents.
- Efficiency: Optimized GRU processing reduces computational overhead.
- Robustness: Handles complex and ambiguous queries effectively through its hybrid architecture.

7.4 How It Compares Standalone Models

7.4.1 Rule-Based Systems:

- Limited to predefined patterns and fails with unseen or ambiguous queries.
- The hybrid model adapts by integrating LSTM and GRU for contextual understanding.

7.4.2 Naïve Bayes:

- Struggles with sequential context and long-term dependencies.
- The hybrid model captures sequential and contextual information using deep learning layers.

7.4.3 LSTM and GRU:

- Standalone LSTM is computationally expensive; GRU is faster but less robust.
- The hybrid model combines their strengths, achieving superior accuracy and efficiency.

7.5 Insights

- The hybrid model outperforms standalone models in both accuracy and efficiency.
- Rule-based verification ensures domain-specific accuracy, reducing false positives
- Processing time is optimized due to GRU's computational efficiency.

8 STATISTICAL VALIDATION

8.1 Hypothesis Testing

1. Null Hypothesis (H_0): There is no significant difference between the performance of the hybrid model and the standalone models (LSTM, GRU).
2. Alternative Hypothesis (H_1): The hybrid model significantly outperforms standalone models in accuracy, precision, recall, and response time.

8.2 Methodology

- Paired t-test:
  - o Used to compare the performance metrics (accuracy, precision, recall, response time) of the hybrid model against LSTM and GRU.
  - o Determines the significance of performance improvements.
- Result

Table 4. Paired T-Test Results

Metric	Model A (LSTM)	Model B (GRU)	Hybrid Model	p- value	Significance
Accuracy (%)	85.7	87.1	92.5	<0.01	Significant
Precision (%)	84.2	85.4	91.8	<0.01	Significant
Recall (%)	83.8	84.9	91.2	<0.01	Significant
Response Time (ms)	50	45	40	<0.05	Significant

As shown in table 4, the paired t-test confirms the hybrid model's significant improvement over LSTM and GRU, with p-values below 0.01 for accuracy, precision, and recall, and below 0.05 for response time.

8.3 ANOVA Test

- Used to compare the mean accuracy values of the hybrid, LSTM, and GRU models across multiple trials.
- Significance Level (α): 0.05 (95% confidence interval).

Result

Table 5. ANOVA Test Results

Metric	F-Statistic	p-value	Significance
Accuracy	125.32	<0.001	Significant

As shown in table 5, the ANOVA test indicates a significant difference in accuracy across models, with an F-statistic of 125.32 and a p-value below 0.001, validating the hybrid model’s superiority.

8.4 Interpretation

1. Significant Differences Confirmed:

- o p-values from t-tests and ANOVA confirm statistically significant performance improvements by the hybrid model.

2. Hybrid Model Superiority:

o The Hybrid model achieved the highest mean accuracy (92.5%), surpassing LSTM (85.7%) and GRU (87.1%) with lower variability.

3. Efficiency:

o The Hybrid model reduced response time to 40ms, significantly faster than LSTM (50ms) and GRU (45ms), confirming its computational efficiency.

The results confirm that the hybrid model significantly outperforms standalone models in all critical metrics, validating its superiority for real-time intent recognition in Moodle chatbots.

The proposed hybrid intent recognition algorithm effectively combines the strengths of deep learning and rule-based systems to overcome the limitations of standalone models. The inclusion of LSTM and GRU ensures a comprehensive understanding of both long-term and short-term dependencies in user queries, while the rule-based layer enhances domain-specific accuracy. Experimental results demonstrate significant improvements in accuracy, precision, recall, and response time, validating the hybrid model's effectiveness in real-world educational scenarios.

Furthermore, the integration of the hybrid model into Moodle fosters enhanced interaction between students and the system, promoting personalized learning experiences. The study highlights how hybrid models can address challenges such as ambiguous queries, rare intent handling, and computational inefficiency in traditional approaches.

The results confirm that the hybrid model significantly outperforms standalone models in all critical metrics, validating its superiority for real-time intent recognition in Moodle chatbots.

9 CONTRIBUTION

9.1 Key Contributions

- Improved Accuracy: Achieved a 5-10% accuracy boost over existing models.
- Context Handling: Enhanced the chatbot’s ability to understand complex queries.
- Domain-Specific Precision: Leveraged rule-based verification for Moodle- specific intents.
- Efficiency: Optimized processing time, enabling real-time responses.

9.2 Implications for Moodle

The enhanced algorithm enables personalized learning by accurately identifying student needs and providing tailored recommendations. This improvement can transform Moodle’s teaching-learning evaluation process, fostering greater student engagement and satisfaction.

10 CONCLUSION AND FUTURE WORK

10.1 Conclusion

This paper introduced a hybrid intent recognition algorithm combining deep learning and rule-based approaches, tailored for Moodle. Experimental results demonstrated significant improvements in accuracy, efficiency, and personalization. The algorithm effectively addresses the limitations of traditional NLU methods, making it a robust solution for real-world educational applications. The integration of the hybrid model into Moodle enables personalized learning by accurately identifying student needs and providing tailored recommendations. These advancements establish a strong foundation for future research in intelligent educational chatbots. Intent detection directly drives personalized learning pathways by recommending topic-specific materials and reminders based on classified intent. This makes Moodle more responsive to individual student needs.

10.2 Future Work

Building on the success of the hybrid model, future work will focus on enhancing context management using reinforcement learning (RL). By integrating RL techniques, the chatbot can dynamically adapt to user behavior and preferences over time, further improving intent recognition and user engagement. Specific areas of exploration include: Dynamic Context Management: Employ RL to enable the chatbot to retain and utilize context across multi-turn conversations, enhancing its ability to respond accurately to complex queries. Expanding the dataset to include more diverse queries. Personalization: Use RL to learn individual user preferences, tailoring responses and recommendations to meet specific needs. Multilingual Support: Extend the hybrid model to support multiple languages, addressing the diverse needs of global educational platforms. Sentiment Analysis: Incorporate sentiment analysis to refine intent recognition and provide empathetic responses, fostering better user experiences.

These enhancements will ensure that the chatbot continues to evolve, addressing emerging challenges and opportunities in the field of educational technology. This contribution serves as a foundation for developing intelligent, context-aware chatbots that can revolutionize the educational experience within LMS platforms like Moodle.

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