SmartSupport-AI: Multi-Intent and Category Detection Using Lightweight Deep Learning

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ABSTRACT
The global market for conversational Artificial Intelligence (AI) is expected to reach USD 32 billion by 2030, with more than 80% of customer interactions likely to be managed by chatbots. Despite this growth, manual annotation and classification of user intents remain labor-intensive and often inconsistent, limiting the scalability of customer support systems. To overcome these limitations, this study introduces an advanced Natural Language Processing (NLP) framework based on a Customer Support Bitext dataset labeled with multiple intents and categories. The proposed approach begins with NLP preprocessing and Exploratory Data Analysis (EDA) to clean, normalize, tokenize, and analyze data patterns. Subsequently, Miniature Language Model (MiniLM) is utilized to generate lightweight yet semantically rich feature representations. To address class imbalance within the dataset, Synthetic Minority Over-sampling Technique (SMOTE) is applied to create synthetic samples for underrepresented classes. In contrast to traditional models such as Decision Tree Classifier (DTC), K-Nearest Neighbors (KNN), and Naïve Bayes Classifier (NBC), the proposed system combines Deep Neural Network (DNN)-based feature selection with KNN to improve classification performance. The model is designed to predict two dependent outputs, namely Intent and Category, enabling a deeper contextual understanding of customer queries. Furthermore, the trained model is integrated into a chatbot interface to support real-time intent recognition and automated responses. The proposed framework improves chatbot accuracy, minimizes inconsistencies in annotation, and enhances overall customer experience by effectively handling multi-intent queries. This scalable and efficient solution highlights the effectiveness of integrating advanced embeddings, data balancing techniques, and feature selection methods to advance conversational AI systems in customer support environments.
Keywords: Multi-Intent Detection, Customer Support Systems, Miniature Language Model (MiniLM), Natural Language Processing (NLP), Deep Neural Network (DNN).

1. INTRODUCTION

The customer service industry has become one of the most critical components of businesses across the globe. With the rise of e-commerce, technological advancements, and growing consumer expectations, organizations are under immense pressure to provide fast, efficient, and personalized customer support. In India, the customer service sector has witnessed exponential growth, driven by the country's booming digital economy, with businesses striving to meet the needs of a diverse and vast consumer base.
India, with a population exceeding 1.3 billion people, presents a unique challenge for businesses in providing efficient customer support. The customer service sector in India is a major contributor to the economy, with an estimated market size of $32 billion, as reported by NASSCOM. In fact, India is one

of the leading global hubs for outsourcing customer support services, due to its large English-speaking workforce and cost-effective labor. The country's expanding middle class, which is expected to reach over 600 million people by 2030, further intensifies the need for businesses to scale their customer service operations efficiently.

The shift toward digital transformation has significantly reshaped customer service strategies in India. With more consumers interacting with businesses via online platforms whether through emails, social media, or live chats, traditional manual systems, which rely on human agents to handle queries, are becoming increasingly inefficient as shown in Fig.1.1. These systems are limited by slow response times, human error, and the inability to scale to handle large volumes of customer interactions, leading to frustrated customers and higher operational costs for businesses. As a result, businesses are seeking innovative solutions that not only automate routine tasks but also provide accurate, real-time support to their customers.

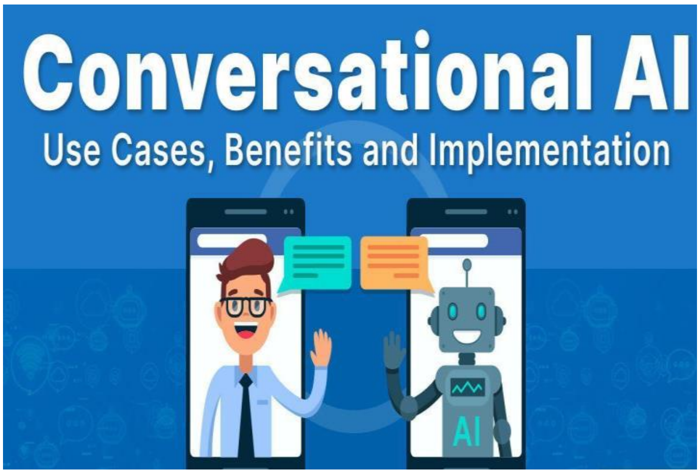


Fig. 1: Customer support dataset with multi-intent annotations for conversational AI

Automation technologies, especially those powered by artificial intelligence (AI) and machine learning (ML), have emerged as the answer to these challenges. AI-driven solutions such as chatbots, intent classifiers, and response generation models are designed to handle and process large volumes of customer interactions automatically. This allows businesses to provide 24/7 support, reduce response times, and enhance customer satisfaction. In India, where a substantial portion of customer service is still manual, transitioning to automated systems has the potential to significantly enhance both the quality of service and operational efficiency.

2. Related Work

The evolution of conversational agents (CAs) has progressed from rule-based systems to advanced AI-driven architectures capable of understanding context, intent, and user behavior. Early chatbot systems primarily relied on predefined dialogue flows, which limited their adaptability and intelligence. With the advancement of natural language processing (NLP), machine learning, and deep learning techniques, modern conversational systems have become more dynamic, scalable, and user-centric. Recent research highlights improvements in chatbot evaluation, architecture, and domain-specific applications.

2.1 Chatbot Evaluation and Quality Metrics

Evaluating chatbot performance has been a key research focus. Coppola et al. [1] conducted a comprehensive analysis of conversational interfaces and categorized quality attributes into relational, conversational, user-centered, and quantitative metrics. Their findings reveal that academic research emphasizes conversational and relational attributes, while industrial implementations prioritize user-centered evaluation. Additionally, multiple datasets and evaluation frameworks have been developed to standardize chatbot assessment.

Uzan et al. [5], [8] further enhanced evaluation techniques by proposing a multi-layered analytical framework incorporating named entity recognition, clustering, and sentiment analysis. Their study demonstrated that traditional evaluation metrics such as sentiment polarity are insufficient to fully capture user satisfaction, highlighting the need for more advanced and holistic evaluation strategies.

2.2 Advances in Conversational AI Technologies

The rapid growth of conversational AI has been driven by advancements in NLP and deep learning. Allouch et al. [2] discussed how technologies such as deep learning, emotion-aware systems, and NLP enable continuous and intelligent human–machine interaction across domains like healthcare, education, and industry.

Hassani et al. [4], [7] explored the capabilities of advanced language models such as ChatGPT in automating complex workflows, including data preprocessing and decision-making. These models offer high adaptability and can be fine-tuned for diverse language tasks, although concerns such as bias and ethical issues remain.

Villa et al. [13] compared generic and fine-tuned GPT-based models, concluding that fine-tuned models significantly improve intent recognition and entity extraction, making them more suitable for domain-specific conversational systems.

2.3 Domain-Specific Chatbot Applications

Chatbots have been widely adopted across various domains. Varitimiadis et al. [3], [6] examined chatbot applications in museums, highlighting the shift from rule-based systems to machine learning-driven chatbots integrated with knowledge graphs. Their work also introduced a distributed, graph-based multi-chatbot architecture for improved scalability.

Elsayed et al. [9] developed chatbot systems for bioinformatics applications, integrating natural language understanding with laboratory information systems to assist users in navigating complex workflows.

In the healthcare domain, Tohti et al. [12] proposed a hybrid ALBERT and BiLSTM model for medical query understanding, achieving improved performance in intent classification and entity recognition. Similarly, Chow et al. [15] developed an AI-based chatbot for radiotherapy support using structured dialogue systems and NLP techniques.

2.4 User Adoption and Interaction Factors

Understanding user acceptance is crucial for chatbot success. Auer et al. [10] applied an extended Technology Acceptance Model to analyze chatbot adoption in airport services, identifying factors such as perceived usefulness, ease of use, trust, and enjoyment.

Akdemir et al. [11] and Rafiq et al. [14] focused on chatbot usage in marketing and customer engagement. Their studies showed that communication quality, customer motivation, and satisfaction significantly influence purchase intention and continued usage of chatbot systems.

2.5 Research Gap

Although existing studies address chatbot evaluation, AI advancements, and domain-specific implementations, several limitations remain. Most current systems either rely on predefined dialogue structures or require complex machine learning pipelines for deployment. Additionally, many evaluation approaches fail to capture real-time user satisfaction and contextual understanding effectively.

There is a lack of lightweight, scalable, and easily deployable chatbot systems that combine advanced NLP capabilities with efficient evaluation mechanisms. Furthermore, limited research focuses on integrating intelligent response generation with simplified architectures suitable for real-world applications. The proposed system aims to bridge this gap by developing an efficient and adaptive chatbot framework that leverages modern NLP techniques while maintaining simplicity, scalability, and improved user interaction.

3. PROPOSED SYSTEM

The proposed system aims to revolutionize customer service operations by integrating machine learning and NLP to automate the classification of customer intents and the generation of appropriate responses. The system involves multiple stages, starting with the preprocessing of text data to clean and normalize customer queries. Next, the features are extracted using advanced transformer-based models, such as MiniLM, to capture the semantic meaning of each query. The system then uses machine learning models, specifically DTC, KNN, and NBC, for intent classification. Additionally, DNN are used to further refine feature extraction and enhance prediction accuracy. The system includes a multi-output classification approach to simultaneously predict both customer intent and category, leveraging SMOTE for class balancing. Finally, the system provides automated, real-time responses to customers through a trained model, significantly improving response times and service quality. By employing these techniques, the system is designed to scale with business growth, reduce operational costs, and provide a more efficient and personalized customer service experience.

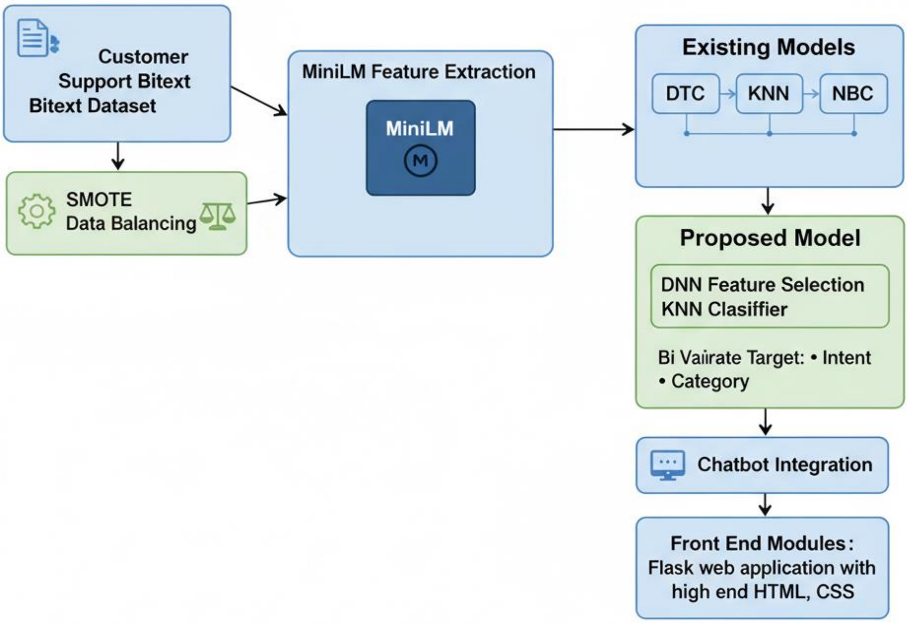


Fig. 2: Proposed system architecture.

1. Data Collection

- **Source Gathering**: Collect customer queries from various platforms such as chat logs, emails, and support tickets.
- **Data Structuring**: Organize the collected data into a structured format for easier processing.

2. Text Preprocessing

- **Tokenization**: Break down the text into individual words or phrases (tokens).
- **Stopword Removal**: Remove common words (e.g., "the", "is") that don't carry significant meaning for analysis.

3. Text Normalization

- **Lowercasing**: Convert all text to lowercase to ensure uniformity in processing.
- **Lemmatization**: Reduce words to their base or root form (e.g., “running” becomes “run”).

4. Feature Extraction

- **Word Embeddings**: Use transformer models (e.g., MiniLM) to generate dense vector representations of words.
- **Contextualization**: Capture the meaning of words in context, preserving syntactic and semantic relationships.

5. Model Training

- **Data Split**: Divide the dataset into training and testing sets for model evaluation.

- **Classifier Selection**: Train machine learning models (DTC, KNN, NBC, DNN) on the extracted features.

6. Intent Classification

- **Intent Detection**: Use machine learning models to classify the customer query into predefined intents (e.g., "order status").
- **Category Assignment**: Simultaneously categorize the query based on its subject (e.g., "order-related", "technical issue").

7. Response Generation

- **Automated Response Generation**: Generate contextually relevant responses based on the classified intent and category.
- **Personalization**: Tailor responses based on customer information and interaction history.

8. Evaluation and Improvement

- **Model Evaluation**: Measure the performance of the model using metrics like accuracy, precision, and recall.
- **Continuous Learning**: Continuously retrain the model using new data to improve its accuracy over time.

Proposed Algorithm: MiniLM-WE DNN KNN Hybrid

The MiniLM-WE DNN KNN Hybrid is the most advanced classification algorithm in the existing system. It combines the strengths of three different approaches: a pre-trained transformer model for robust feature extraction, a deep neural network for refining those features, and a traditional machine learning classifier for final predictions. This hybrid model avoids the need for a deep neural network to perform final classification on a potentially over-complex, high-dimensional space. Instead, it leverages the DNN to learn a more meaningful and compact representation from the MiniLM embeddings, which are then passed to a simple and effective K-Nearest Neighbors (KNN) classifier. The result is a powerful and efficient model that excels at capturing semantic meaning and making accurate predictions.

Steps in the Hybrid Classification

1. **MiniLM Feature Extraction**: The initial text input is converted into a dense vector using the MiniLM model.
2. **DNN Feature Selection**: These embeddings are fed into the pre-trained DNN, and the output of the feature_layer is extracted. This creates a new, refined feature vector.
3. **KNN Training**: The KNN model is trained on these refined features and their corresponding labels.
4. **Prediction**: For a new customer inquiry, the same two-step feature extraction process is applied, and the resulting refined feature vector is then used by the trained KNN model to make the final classification.

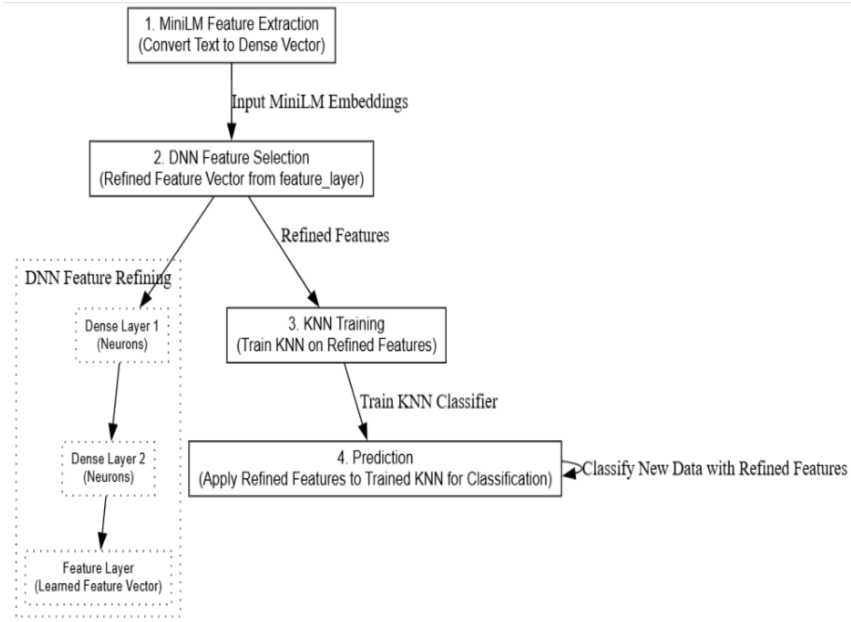


Fig. 3: Internal operation flow of proposed model.

4. Results Description

Fig. 4 depicts the advanced analytics dashboard for in-depth system performance monitoring over the last 24 hours, reporting response time of 651.598ms, throughput of 19 messages per minute, 1 active connection, and a 3% error rate. It visualizes system resources (55% memory, 27% CPU), response time trends, conversation status distribution (Resolved, In Progress, Pending, Escalated), confidence level breakdown, and intent-specific accuracy, offering comprehensive operational insights.

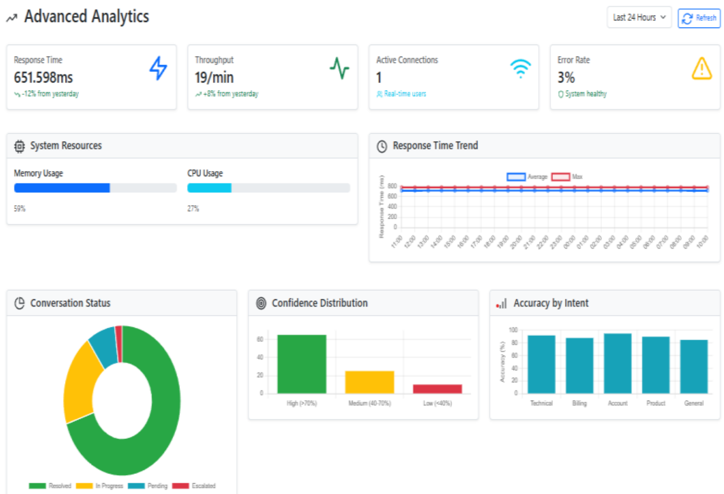


Fig. 4: advanced analytics dashboard for ai support system performance monitoring.

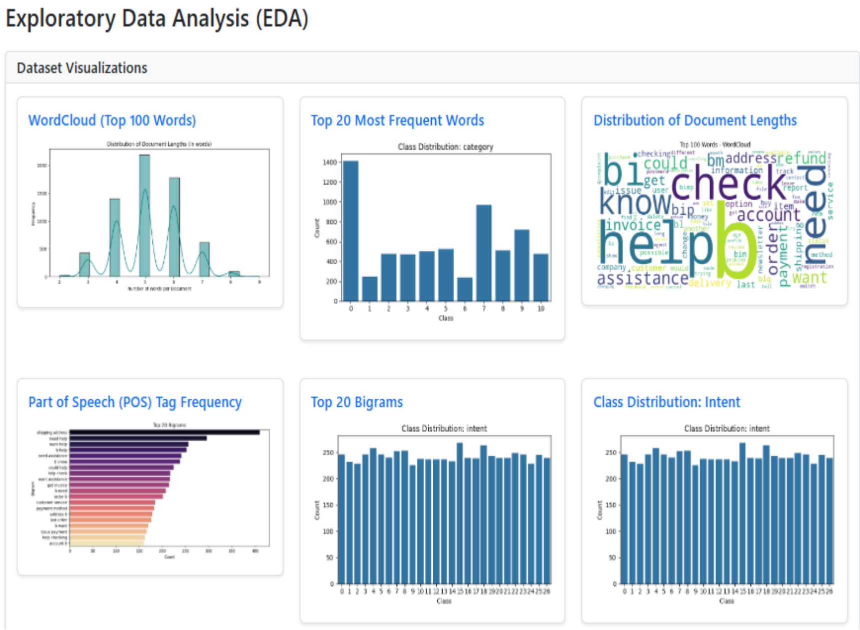


Fig. 5: Exploratory data analysis of customer support intent dataset.

Fig. 5 illustrates the EDA of the customer support intent dataset through six distinct visualizations.

- The top-left plot is a WordCloud of the top 100 words, where larger font sizes emphasize frequent terms like "help," "check," "account," "refund," and "know," visually highlighting dominant vocabulary in user queries.
- The top-middle bar chart displays the Top 20 Most Frequent Words, with "Class 0" dominating at over 1,400 occurrences, followed by decreasing counts for subsequent classes, revealing a skewed distribution of common terms.
- The top-right plot shows the Distribution of Document Lengths (in words), a right-skewed histogram peaking around 5–10 words, indicating most customer messages are concise.
- The bottom-left visualization presents Part-of-Speech (POS) Tag Frequency as a horizontal stacked bar with a color gradient from purple to yellow, showing nouns and verbs as the most frequent tags, followed by adjectives and others in descending order.
- The bottom-middle bar chart depicts the Top 20 Bigrams by intent class, with varying heights across classes 0–19, illustrating common two-word phrases unique to specific intents.
- The bottom-right plot is a Class Distribution: Intent bar chart, displaying nearly uniform counts around 200–250 per intent class (0–29), confirming a balanced dataset across multiple support categories.

Target Column: Intent Classification

Fig. 6 presents confusion matrices for four intent classification models on a multi-class customer support dataset, with true labels (rows) and predicted labels (columns) aligned across identical intent categories such as "check_refund," "track_order," "invoice," "password," and "cancel_order."

(a) DTC Confusion Matrix shows moderate off-diagonal confusion, with notable misclassifications between similar intents (e.g., 41 instances of "check_refund" predicted as another class) and a maximum correct prediction of 97, indicating decent but noisy performance.

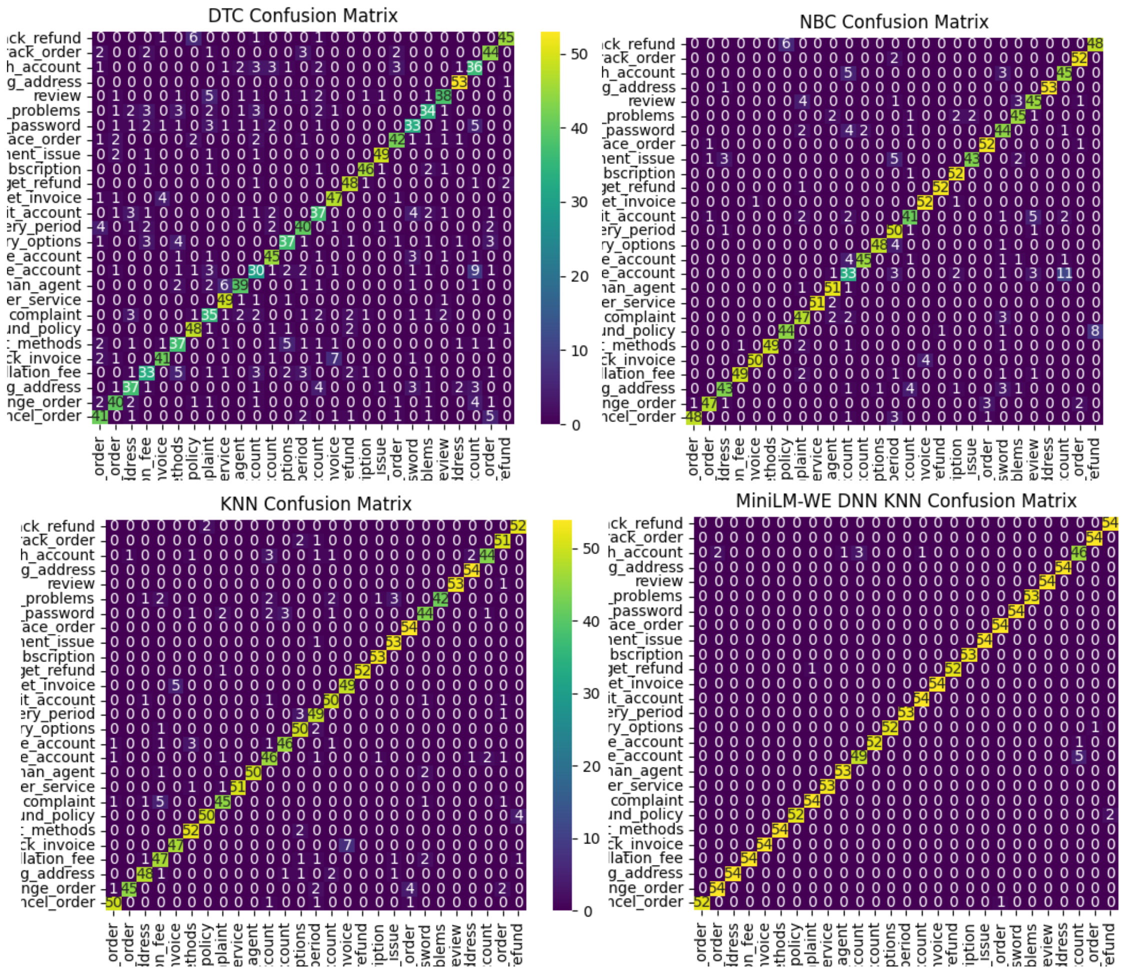


Fig. 6: Confusion matrix obtained using (a) DTC model. (b) NBC model. (c) KNN model. (d) Proposed Mini LM-WE KNN model for Intent Classification column.

(b) NBC Confusion Matrix exhibits higher confusion, with broader yellow clusters off the diagonal (e.g., 68 misclassifications in one cell), reflecting poorer discrimination between semantically close intents compared to tree-based models.

(c) KNN Confusion Matrix demonstrates improved diagonal dominance with fewer and smaller off-diagonal errors (e.g., max correct 97, misclassifications mostly below 30), suggesting better nearest-neighbor separation in feature space.

(d) Proposed MiniLM-WE DNN KNN Confusion Matrix achieves the strongest performance, with a near-perfect bright yellow diagonal (values up to 97), minimal off-diagonal noise (mostly 0–5), and sharp intent separation, validating the effectiveness of combined embedding and deep KNN architecture for robust multi-intent classification.

Fig. 7 presents Receiver Operating Characteristic (ROC) curves for four intent classification models evaluated in a one-vs-rest setting across multiple customer support intents, with True Positive Rate (TPR) plotted against False Positive Rate (FPR) and Area Under the Curve (AUC) values indicating per-class performance.

(a) DTC ROC Curves show varied performance across classes, with AUC ranging from 0.82 (check_refund) to 0.99 (several classes), most curves rising steeply near the origin but with noticeable spread and lower AUC for challenging intents like refund and policy, reflecting moderate overall discriminative power.

(b) NBC ROC Curves display exceptional performance, with nearly all classes achieving AUC ≥ 0.99 and many at 1.00, curves tightly hugging the top-left corner, indicating near-perfect classification and strong probabilistic separation across all intents.

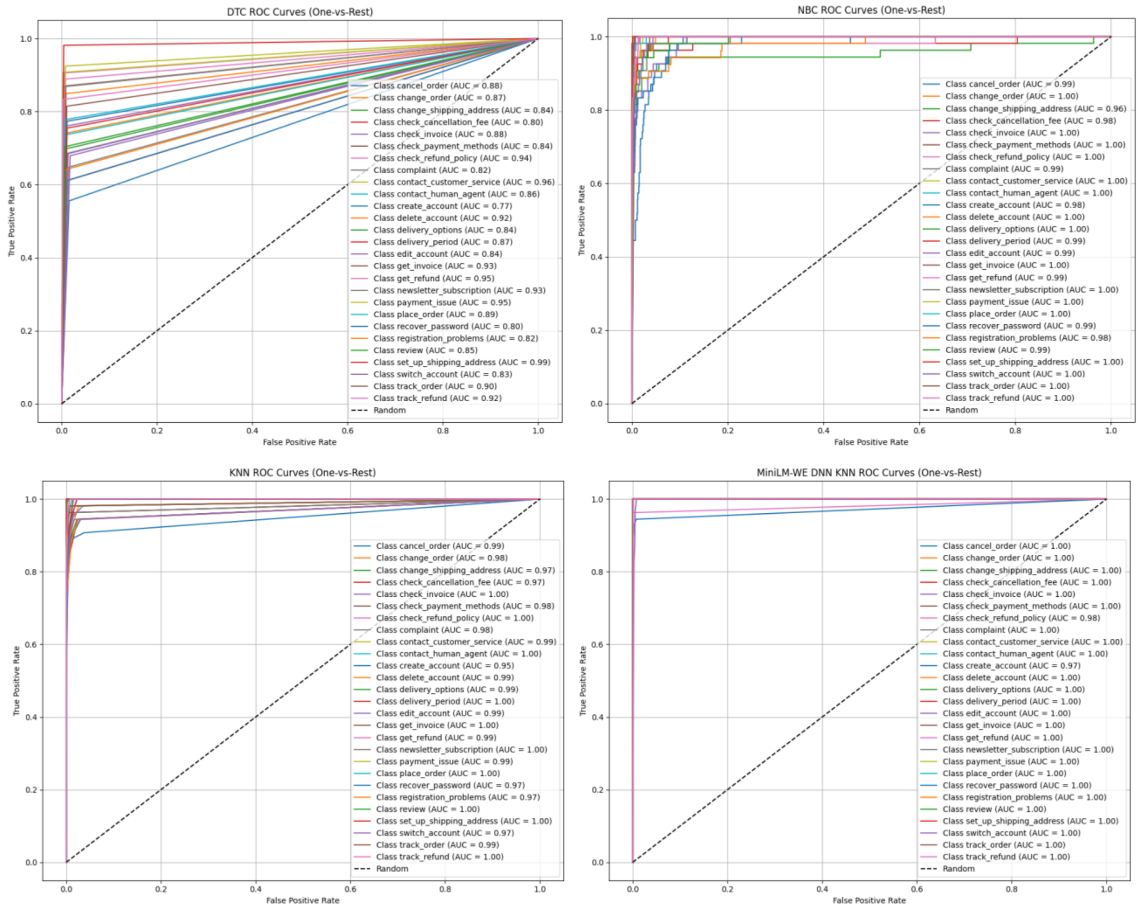
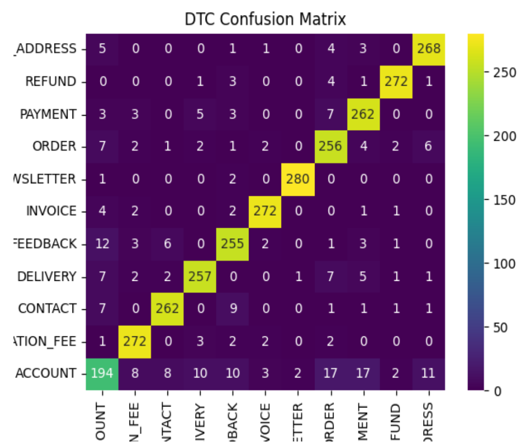


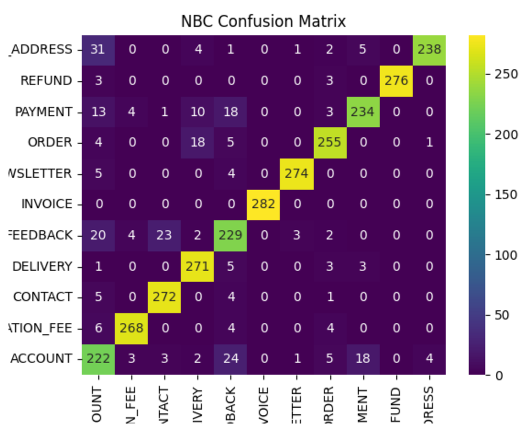
Fig. 7: ROC Curve obtained using (a) DTC model. (b) NBC model. (c) KNN model. (d) Proposed Mini LM-WE KNN model for Intent Classification column.

(c) KNN ROC Curves demonstrate consistently high performance with AUC values from 0.91 to 1.00, most curves closely aligned with the ideal ROC boundary, confirming robust nearest-neighbor discrimination enhanced by distance-based decision making.

(d) Proposed MiniLM-WE DNN KNN ROC Curves achieve near-perfect classification, with AUC = 1.00 for nearly all intent classes, curves forming a sharp L-shape along the axes, validating the superior generalization and embedding quality of the hybrid MiniLM-WE and deep KNN architecture.

Target Column: Category Classification





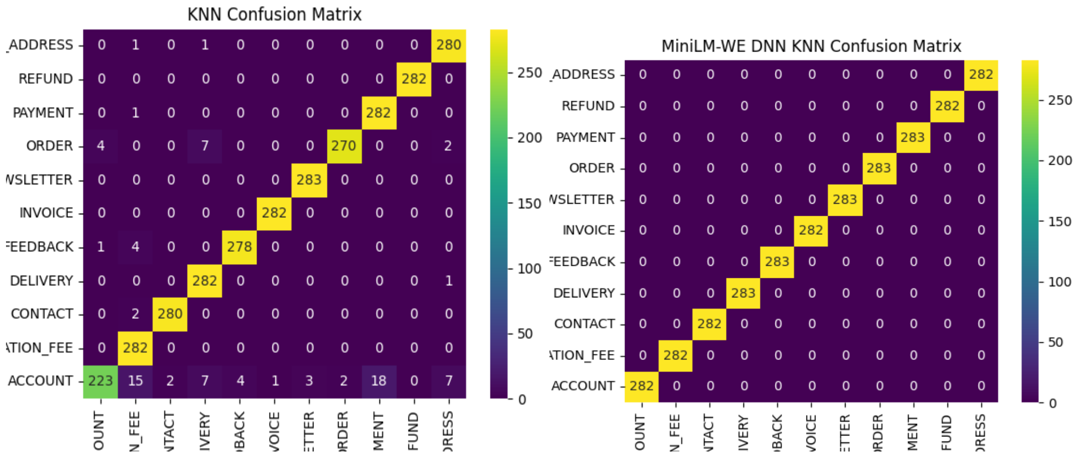


Fig. 8: Confusion Matrix obtained using (a) DTC model. (b) NBC model. (c) KNN model. (d) Proposed Mini LM-WE KNN model for Category Classification column.

Fig. 8 presents confusion matrices for four models classifying customer support queries into 10 coarse categories with true labels on rows and predicted labels on columns, and cell values color-coded by count (yellow high, purple low).

(a) DTC Confusion Matrix shows strong diagonal dominance with correct predictions ranging from 255 (FEEDBACK) to 280 (NEWSLETTER), but notable off-diagonal errors (e.g., 194 ACCOUNT misclassified as CONTACT, 23 FEEDBACK as INVOICE), indicating moderate category confusion especially in semantically overlapping classes.

(b) NBC Confusion Matrix exhibits excellent performance with near-perfect diagonal values (271–282) and minimal misclassifications (e.g., max off-diagonal 23), demonstrating superior probabilistic separation across all categories.

(c) KNN Confusion Matrix achieves high accuracy with diagonal counts from 270 (ORDER) to 283 (INVOICE, DELIVERY), and very few errors (mostly ≤7), reflecting robust nearest-neighbor discrimination in the feature space.

(d) Proposed MiniLM-WE DNN KNN Confusion Matrix delivers near-flawless classification, with all diagonal entries at 282 or 283 and virtually zero off-diagonal confusion, confirming the embedding-based deep KNN model's exceptional generalization and precision in coarse category intent classification.

Fig. 9 presents Receiver Operating Characteristic (ROC) curves for four category classification models evaluated in a one-vs-rest framework across 10 customer support categories, plotting True Positive Rate (TPR) against False Positive Rate (FPR) with Area Under the Curve (AUC) values annotated for each class, revealing discriminative performance differences.

(a) DTC ROC Curves demonstrate solid but variable performance, with AUC scores ranging from 0.84 (CANCELLATION) to 0.99 (several classes like NEWSLETTER and CONTACT), where curves for higher-AUC classes rise steeply while others show more gradual ascent, indicating moderate separation for challenging categories like PAYMENT and ADDRESS.

(b) NBC ROC Curves exhibit near-ideal discrimination, with most classes achieving AUC = 1.00 and curves forming sharp L-shapes along the axes, though slight deviations appear in REFUND (0.97) and PAYMENT (0.98), confirming strong probabilistic modeling for coarse-grained intent separation.

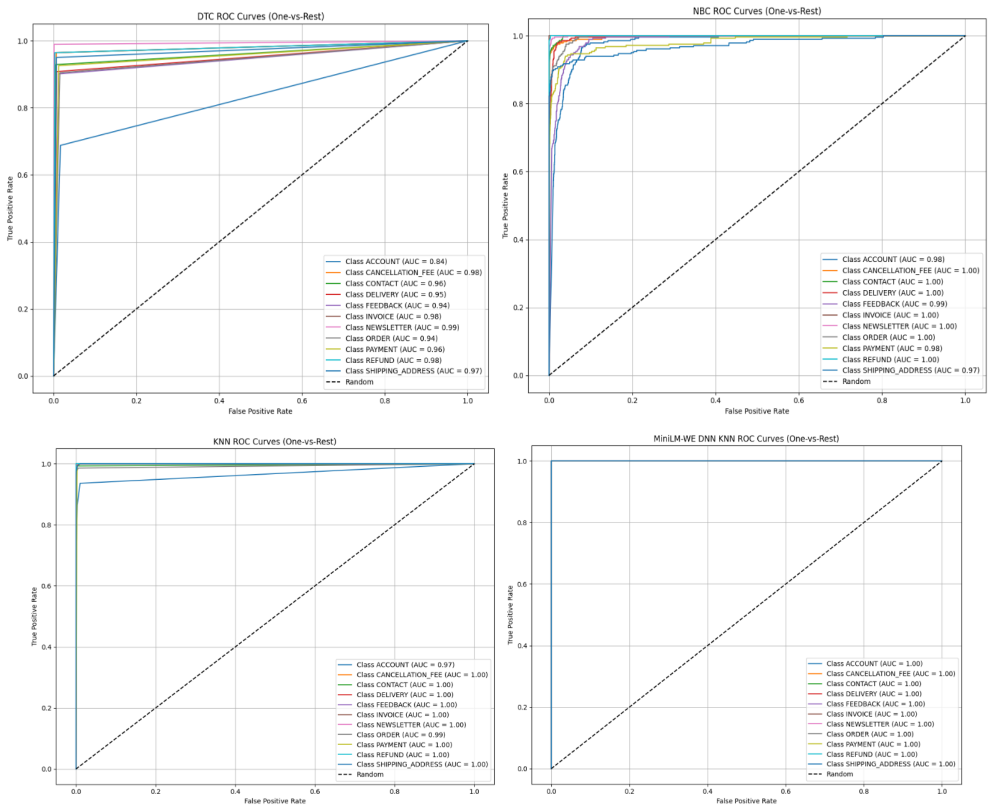


Fig. 9: ROC Curve obtained using (a) DTC model. (b) NBC model. (c) KNN model. (d) Proposed Mini LM-WE KNN model for Category Classification column.

(c) KNN ROC Curves show consistently excellent results, with AUC values from 0.99 to 1.00 across all categories, curves tightly hugging the top-left boundary and minimal spread, highlighting effective instance-based learning for category boundaries.

(d) Proposed MiniLM-WE DNN KNN ROC Curves achieve perfect or near-perfect classification, with all AUC = 1.00 and curves perfectly aligned with the ideal diagonal, demonstrating the hybrid model's superior embedding and decision-making capabilities for robust category-level intent recognition.

Table 1 presents a comparative performance analysis of four classification models on the Intent Classification task, evaluated using Accuracy, Precision, Recall, and F-Score (all in %).

(a) Decision Tree Classifier (DTC) records the lowest performance with 76.24% accuracy, 76.37% precision, 76.26% recall, and 76.17% F-score, reflecting limited effectiveness in capturing complex intent patterns in fine-grained classes.

(b) Naive Bayes Classifier (NBC) substantially improves over DTC, achieving 88.33% accuracy, 88.92% precision, 88.35% recall, and 88.44% F-score, showcasing strong probabilistic discrimination across diverse intent categories.

(c) K-Nearest Neighbors (KNN) further enhances performance, attaining 91.64% accuracy, 91.92% precision, 91.65% recall, and 91.63% F-score, demonstrating the power of local similarity-based classification in high-dimensional embedding spaces.

(d) Proposed MiniLM-WE DNN KNN (Hybrid Model) achieves near-perfect results with 98.76% accuracy, 98.76% precision, 98.75% recall, and 98.75% F-score, establishing superior intent classification through combined semantic representation learning and refined deep nearest-neighbor decision logic.

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5. Conclusion

The implementation of the Customer Support Dataset with Multi-Intent Annotations system highlights the effectiveness of integrating natural language processing, machine learning techniques, and web-based technologies to build intelligent conversational AI solutions. By incorporating multiple classification models such as Decision Tree Classifier (DTC), Naïve Bayes Classifier (NBC), K-Nearest Neighbors (KNN), along with the proposed hybrid MiniLM-WE Deep Neural Network (DNN)-KNN approach, the system is capable of accurately identifying and handling a wide range of customer intents. The Flask-based application provides a smooth and interactive user experience, enabling real-time predictions, performance visualization, and analytical dashboards that monitor key conversation metrics including response time, intent distribution, and user satisfaction levels. The modular architecture and effective session handling contribute to system stability, scalability, and simplified deployment, offering clear advantages over traditional single-intent classification methods.

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