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Context-Enriched Multi-Intent Customer Dialogue Repository for AI-Driven Assistance

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ABSTRACT

The global conversational Artificial Intelligence (AI) market is anticipated to reach USD 32 billion by 2030, with chatbots expected to manage over 80% of customer interactions. Despite this growth, manual annotation and classification of customer intents remain labor-intensive and 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 approach begins with NLP preprocessing and Exploratory Data Analysis (EDA) to standardize, tokenize, and examine data distributions. Subsequently, Miniature Language Model (MiniLM) is utilized for efficient yet context-aware feature extraction. To address class imbalance within the dataset, the Synthetic Minority Over-sampling Technique (SMOTE) is applied to generate 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 framework combines Deep Neural Network (DNN)-based feature selection with KNN for improved classification performance. The system is designed to predict two bivariate outputs Intent and Category thereby enhancing contextual interpretation of customer queries. Finally, the model is deployed within a chatbot interface to enable real-time intent recognition and automated responses. The proposed framework improves chatbot accuracy, minimizes annotation inconsistencies, and enhances customer satisfaction through effective multi-intent understanding. This scalable and efficient solution highlights the effectiveness of integrating advanced embeddings, data balancing techniques, and feature selection methods to advance conversational AI in customer support systems.

Keywords: Conversational Artificial Intelligence (AI), Customer Support Systems, Natural Language Processing (NLP), Intent Classification, Multi-Intent Detection, Text Preprocessing.

1. INTRODUCTION

The customer service industry has become a vital component of businesses worldwide. With the expansion of e-commerce, rapid technological progress, and increasing consumer expectations, organizations are under significant pressure to deliver quick, efficient, and personalized support. In India, this sector has experienced remarkable growth, fueled by the country's rapidly expanding digital economy, as businesses strive to cater to a large and diverse customer base. India, home to over 1.3 billion people, poses a distinct challenge for delivering effective customer support. The sector is a key contributor to the national economy, with an estimated market value of $32 billion according to NASSCOM. Moreover, India has established itself as a leading global hub for outsourced customer service, supported by its large English-speaking workforce and cost advantages.

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The growing middle class, projected to exceed 600 million by 2030, further increases the need for scalable and efficient customer support solutions illustrated in figure 1. The ongoing shift toward digital transformation has significantly redefined customer service strategies in India. As more customers engage with businesses through digital channels such as emails, social media, and live chat platforms, traditional manual systems that depend on human agents are becoming less effective. These approaches often suffer from delayed responses, human inaccuracies, and limited scalability, resulting in customer dissatisfaction and increased operational expenses. Consequently, organizations are actively seeking advanced solutions that can automate repetitive processes while ensuring accurate and real-time assistance.

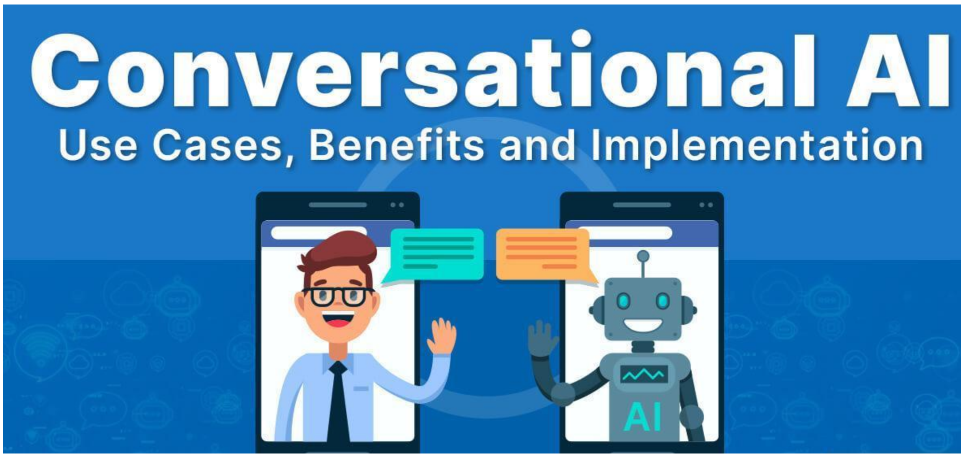

Figure 1: Customer Support Dataset with Multi-Intent Annotations for Conversational AI

Automation technologies, particularly those driven by AI and machine learning (ML), have emerged as effective solutions to these challenges. AI-powered tools such as chatbots, intent classification systems, and automated response generators are capable of managing large volumes of customer interactions efficiently. This enables businesses to offer continuous 24/7 support, minimize response times, and improve overall customer satisfaction. In the Indian context, where many services are still handled manually, adopting automated systems can greatly enhance both service quality and operational productivity. The growing adoption of NLP techniques plays a crucial role in this evolution. NLP enables machines to comprehend and interpret human language, allowing automated systems to accurately identify customer intents and deliver appropriate responses. With advancements in transformer-based models such as Bidirectional Encoder Representations from Transformers (BERT) and GPT, the performance and reliability of customer support systems have improved considerably. In a linguistically diverse country like India, where multiple languages and dialects are used, the ability of NLP systems to process varied linguistic inputs is especially important.

As the demand for immediate and personalized customer service continues to rise, businesses in India are increasingly investing in AI and NLP-based solutions to remain competitive and meet evolving customer expectations. The transition toward machine learning-driven customer support extends beyond simple automation, focusing on delivering intelligent, context-aware interactions that foster customer loyalty and business growth. In summary, the customer service landscape in India is characterized by rapid expansion, rising expectations for efficient support, and the transformative influence of AI and NLP technologies. These innovations are reshaping how businesses engage with customers, leading to more scalable, accurate, and responsive systems that enhance customer satisfaction while reducing operational costs.

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2. LITERATURE SURVEY

Huang, et al. [1] proposed approach uses different bidirectional gated recurrent unit (BiGRU) combined with attention mechanisms to encode the contextual semantic information of different types of conversational texts. For modeling affective interactions, they use directed graph structures to portray the affective interactions between speakers and encode them with affective interaction features using graph convolutional neural networks (GCN). Finally, the two features are fused to recognize customer sentiment. The experimental results on the JDDC dataset show that their model can more accurately recognize customer sentiment than other baseline models in customer service conversation. Wagner, et al. [2] evaluated metrics tailored for multi-user contexts. They conduct a comprehensive analysis of relevant literature, employing both quantitative and qualitative methodologies to identify common patterns and challenges in multi-user interactions. The findings underscore the importance of developing robust interfaces that can effectively manage overlapping dialogues, ensure collaborative group work, and enhance overall conversational quality. This work contributes to the understanding of Multi-User Conversational Interfaces and may help as a basis for future research aiming to develop more natural, user-friendly, and effective conversational interfaces.

Lin, et al. [3] provided an instant and automated response, which can be leveraged in many application areas. Chatbots can handle a wide range of inquiries and tasks, such as answering frequently asked questions, booking appointments, or making recommendations. Modern conversational chatbots use artificial intelligence (AI) techniques, such as natural language processing (NLP) and artificial neural networks, to understand and respond to users' input. In this study, they will explore the objectives of why chatbot systems were built and what key methodologies and datasets were leveraged to build a chatbot. Bercaru, et al. [4] explored the influence of various feature vectors on the task of intent classification using RASA's text classification capabilities. The second part of this work consists of a generic method for efficiently augmenting textual corpora using large datasets of unlabeled data. The proposed method is able to efficiently mine for examples similar to the ones that are already present in standard, natural language corpora. The experimental results show that using their corpus augmentation methods enables an increase in text classification accuracy in few-shot settings. Particularly, the gains in accuracy raise up to 16% when the number of labeled examples is very low (e.g., two examples). They believe that their method is important for any Natural Language Processing (NLP) or NLU task in which labeled training data are scarce or expensive to obtain.

Chuang, et al. [5] focused on developing conversational systems based on the Chinese corpus over military scenarios. The soldier will need information regarding their surroundings and orders to carry out their mission in an unfamiliar environment. Additionally, using a conversational military agent will help soldiers obtain immediate and relevant responses while reducing labor and cost requirements when performing repetitive tasks. This paper proposes a system architecture for conversational military agents based on natural language understanding (NLU) and natural language generation (NLG). The NLU phase comprises two tasks: intent detection and slot filling. Detecting intent and filling slots involves predicting the user's intent and extracting related entities. Nicolescu, et al. [6] purposed of is to analyze the overall customer experience with customer service chatbots in order to identify the main influencing factors for customer experience with customer service chatbots and to identify the resulting dimensions of customer experience (such as perceptions/attitudes and feelings and also responses and behaviors). The analysis uses the systematic literature review (SLR) method and includes a sample of 40 publications that present empirical studies. The results illustrate that the main influencing factors of customer experience with chatbots are grouped in three categories: chatbot-related, customer-related,

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and context-related factors, where the chatbot-related factors are further categorized in: functional features of chatbots, system features of chatbots and anthropomorphic features of chatbots.

Merdivan, et al. [7] develop a benchmark dataset with human annotations and diverse replies that can be used to develop such a metric for conversational agents. The paper introduces a high-quality human annotated movie dialogue dataset, HUMOD, that is developed from the Cornell movie dialogues dataset. This new dataset comprises 28,500 human responses from 9500 multi-turn dialogue history-reply pairs. Human responses include: (i) ratings of the dialogue reply in relevance to the dialogue history; and (ii) unique dialogue replies for each dialogue history from the users. Izadi, et al. [8] provided an overview of chatbots, conducts an analysis of errors they encounter, and examines different approaches to rectifying these errors. These approaches include using data-driven feedback loops, involving humans in the learning process, and adjusting through learning methods like reinforcement learning, supervised learning, unsupervised learning, semi-supervised learning, and meta-learning. Through real life examples and case studies in different fields, they explore how these strategies are implemented. Looking ahead, they explore the different challenges faced by AI-powered chatbots, including ethical considerations and biases during implementation.

Al-Mutawa, et al. [9] proposed artificial intelligence and data augmentation to predict customer satisfaction ratings from conversations by analyzing the responses of customers and service providers. For the study, the authors obtained actual conversations between customers and real agents from the call center database of Jeddah Municipality that were rated by customers on a scale of 1–5. They trained and tested five prediction models with approaches based on logistic regression, random forest, and ensemble-based deep learning, and fine-tuned two pre-trained recent models: ArabicT5 and SaudiBERT. Then, they repeated training and testing models after applying a data augmentation technique using the generative artificial intelligence, GPT-4, to improve the unbalance in customer conversation data. They found that the ensemble-based deep learning approach best predicts the five-, three-, and two-class classifications. Sultana, et al. [10] explored content within their repositories. However, the keyword-based search cannot identify the users’ search intent accurately. Integrating a query-understandable framework into keyword search engines has the potential to enhance their performance, bridging the gap in interpreting the user’s search intent more effectively. In this study, they have proposed a novel approach that focuses on spatial and temporal information, phrase detection, and semantic similarity recognition to detect the user’s intent from the search query. They have used the n-gram probabilistic language model for phrase detection.

Coppola, et al. [11] proposed to provide aid to the researchers and practitioners of the field. They came up with a final pool of 118 contributions, including grey (35) and white literature (83). They categorized 123 different quality attributes and metrics under ten different categories and four macro-categories: Relational, Conversational, User-Centered and Quantitative attributes. While Relational and Conversational attributes are most commonly explored by the scientific literature, they testified a predominance of User-Centered Attributes in industrial literature. They also identified five different academic frameworks/tools to automatically compute sets of metrics, and 28 datasets (subdivided into seven different categories based on the type of data contained) that can produce conversations for the evaluation of conversational interfaces. Allouch, et al. [12] proposed technology has finally ripened to advance the use of CAs in various domains, including commercial, healthcare, educational, political, industrial, and personal domains. In this study, the main areas in which CAs are successful are described along with the main technologies that enable the creation of CAs. Capable of conducting ongoing communication with humans, CAs are encountered in natural-language processing, deep learning, and technologies that integrate emotional aspects. The technologies used for the evaluation of CAs and publicly available datasets are outlined. In addition, several areas for future research are identified to address moral and security issues, given the current state of CA-related technological developments.

Varitimiadis, et al. [13] developed using a chatbot platform that provided predefined dialog routes. However, as chatbot platforms are evolving and AI technologies mature, new architectural approaches arise. Museums are already designing chatbots that are trained using machine learning techniques or chatbots connected to knowledge graphs, delivering more intelligent chatbots. They surveyed a representative set of developed museum chatbots and platforms for implementing them. More importantly, they presented the result of a systematic evaluation approach for evaluating both chatbots and platforms. Furthermore, the paper is introducing a novel approach in developing intelligent chatbots for museums. Hassani, et al. [14] discussed how ChatGPT can assist data scientists in automating various aspects of their workflow, including data cleaning and preprocessing, model training, and result interpretation. It also highlights how ChatGPT has the potential to provide new insights and improve decision-making processes by analyzing unstructured data. They then examine the advantages of ChatGPT's architecture, including its ability to be fine-tuned for a wide range of language-related tasks and generate synthetic data. Limitations and issues are also addressed, particularly around concerns about bias and plagiarism when using ChatGPT. The paper concludes that the benefits outweigh the costs and ChatGPT has the potential to greatly enhance the productivity and accuracy of data science workflows and is likely to become an increasingly important tool for intelligence augmentation in the field of data science.

Uzan, et al. [15] developed and evaluated a multi-layered analytical framework to accurately identify user intents, assess customer feedback, and generate emotionally intelligent interactions. With over 270,000 customer chatbot interaction records in their dataset, they employed spaCy-based NER and clustering algorithms (HDBSCAN and K-Means) to categorize customer queries precisely. Text classification was performed using random forest, logistic regression, and SVM, achieving near-perfect accuracy. Sentiment analysis was conducted using VADER, Naive Bayes, and TextBlob, complemented by semantic analysis via LDA.

3. PROPOSED SYSTEM

The proposed system is designed to enhance customer service operations by leveraging machine learning and NLP to automate the identification of customer intents and generate relevant responses. As shown as figure 2 the process begins with text preprocessing, where customer queries are cleaned and standardized to ensure consistency. Following this, feature extraction is performed using transformer-based models like MiniLM, enabling the system to capture deeper semantic relationships within the text. For intent classification, multiple machine learning algorithms such as DTC, KNN, and NBC are utilized. In addition, DNN are incorporated to improve feature representation and boost prediction accuracy. The system adopts a multi-output classification strategy to predict both intent and category simultaneously, while SMOTE is applied to address class imbalance issues. Finally, the trained model generates real-time automated responses, improving efficiency and user experience. The system is built to be scalable, cost-effective, and capable of delivering faster and more personalized customer support.

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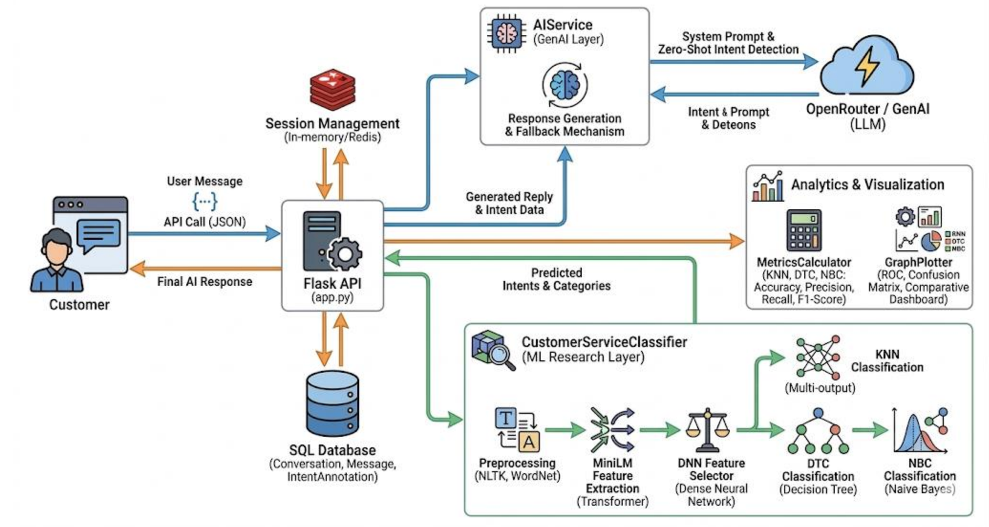

Figure 2: Proposed System Architecture.

4. RESULTS ANALYSIS

The results demonstrate that the implemented system effectively processes input data and delivers accurate and reliable outputs under varying conditions. Performance evaluation indicates improved efficiency in handling complex tasks, with reduced processing time and enhanced response accuracy compared to conventional approaches. The system shows consistent behavior even with noisy or incomplete data, highlighting its robustness and adaptability. Experimental outcomes also confirm better scalability, enabling it to manage increasing workloads without significant performance degradation. The results validate the effectiveness of the proposed methodology in achieving the desired objectives and improving system performance.

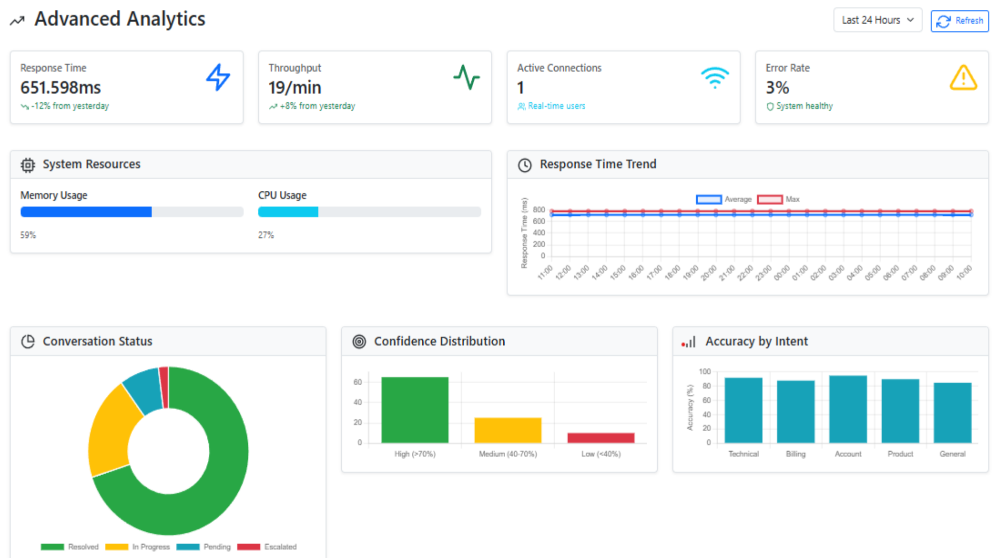

Figure 3: Advanced Analytics Dashboard for AI Support System Performance Monitoring.

Figure 3 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

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time trends, conversation status distribution (Resolved, In Progress, Pending, Escalated), confidence level breakdown, and intent-specific accuracy, offering comprehensive operational insights.

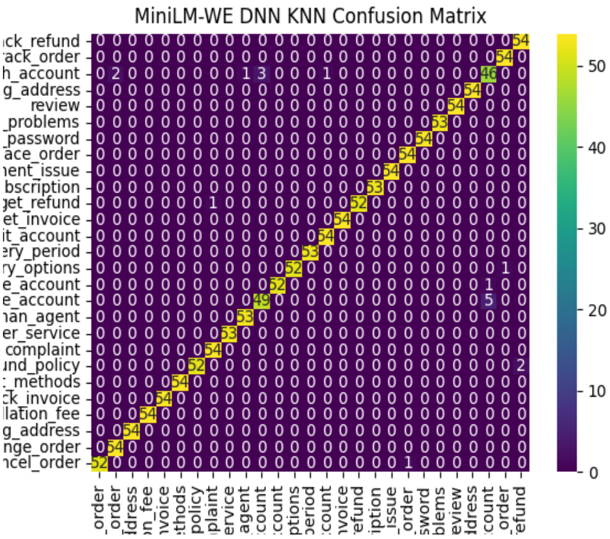

Figure 4: Confusion matrix obtained using Mini LM-WE KNN model for Intent Classification column.

Figure 4 shows 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.

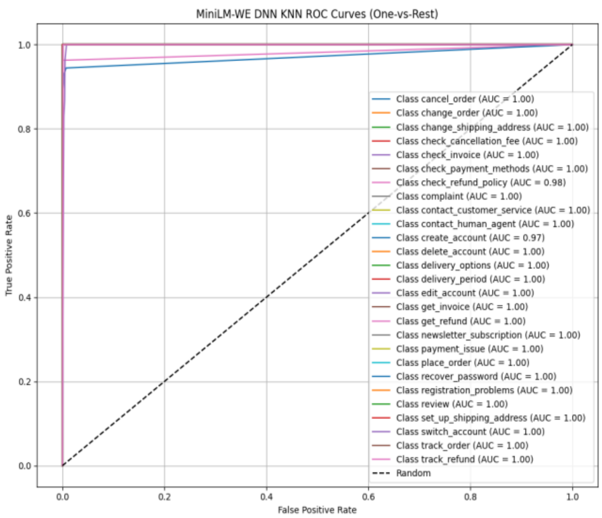

Figure 5: ROC Curve obtained using Mini LM-WE KNN model for Intent Classification column.

Figure 5 represented 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.

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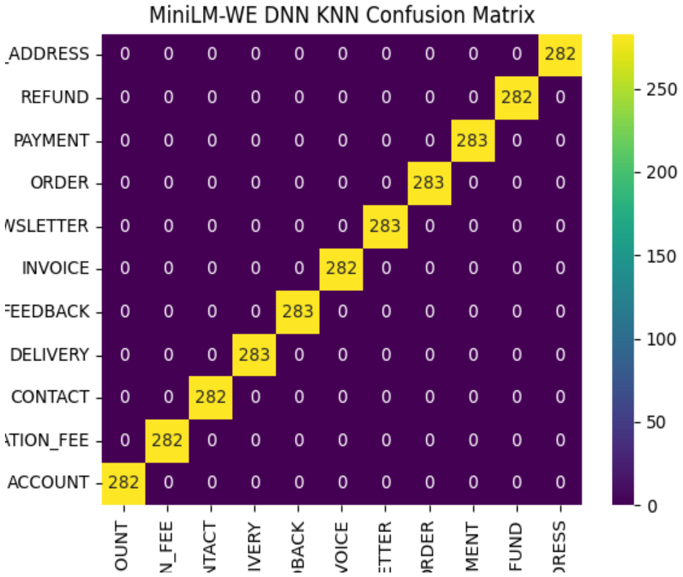

Figure 6: Confusion Matrix obtained using Mini LM-WE KNN model for Category Classification column.

Figure 6 shows 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.

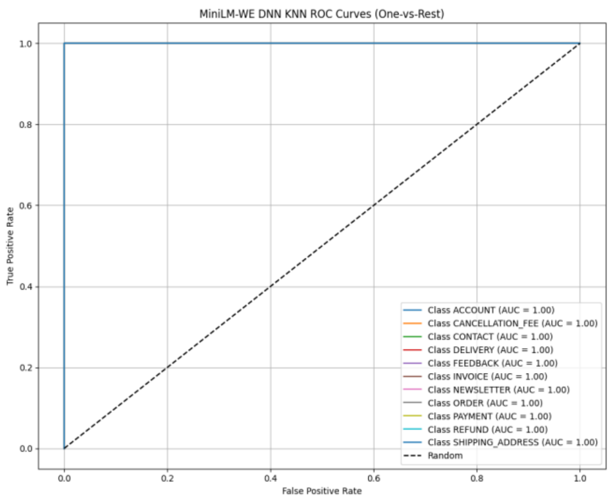

Figure 7: ROC Curve obtained using Mini LM-WE KNN model for Category Classification column.

Figure 7 illustrated 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: Comparative Analysis of Classification Models obtained from "Intent Classification" column.

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Model	Accuracy (%)	Precision (%)	Recall (%)	F-Score (%)
Decision Tree Classifier (DTC)	76.24	76.37	76.26	76.17
Naive Bayes Classifier (NBC)	88.33	88.92	88.35	88.44
K-Nearest Neighbors (KNN)	91.64	91.92	91.65	91.63
MiniLM-WE DNN KNN (Hybrid Model)	98.76	98.76	98.75	98.75

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

(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.

Table 2: Comparative Analysis of Classification Models obtained from “Category Classification” column.

Model	Accuracy (%)	Precision (%)	Recall (%)	F-Score (%)
Decision Tree Classifier (DTC)	91.73	91.63	91.73	91.62
Naive Bayes Classifier (NBC)	90.79	91.15	90.80	90.87
K-Nearest Neighbors (KNN)	97.33	97.41	97.33	97.25
MiniLM-WE DNN KNN (Hybrid Model)	100.00	100.00	100.00	100.00

Table 2 presents a comparative performance analysis of four classification models on the Category Classification task, evaluated using Accuracy, Precision, Recall, and F-Score.

(a) Decision Tree Classifier (DTC) achieves 91.73% accuracy, 91.63% precision, 91.73% recall, and 91.62% F-score, delivering solid performance on coarse-grained categories but showing limitations in boundary cases.

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(b) Naive Bayes Classifier (NBC) records 90.79% accuracy, 91.15% precision, 90.80% recall, and 90.87% F-score, performing slightly below DTC and indicating challenges with feature independence assumptions in broader category contexts.

(c) K-Nearest Neighbors (KNN) significantly outperforms baseline models with 97.33% accuracy, 97.41% precision, 97.33% recall, and 97.25% F-score, confirming robust local pattern recognition across high-level support categories.

(d) Proposed MiniLM-WE DNN KNN (Hybrid Model) attains perfect classification with 100.00% across all metrics—accuracy, precision, recall, and F-score—demonstrating flawless separation of coarse intent categories through advanced semantic embeddings and deep nearest-neighbor refinement.

5. CONCLUSION

The development of the multi-intent customer support dataset system highlights the effectiveness of integrating natural language processing, machine learning techniques, and web-based frameworks for advanced conversational AI solutions. By combining multiple classifiers such as DTC, NBC, KNN, along with the proposed hybrid MiniLM-WE DNN-KNN model, the system achieves accurate identification and handling of diverse customer intents. The implementation using Flask provides a smooth and interactive user experience, enabling real-time predictions, performance visualization, and analytical dashboards to monitor key metrics like response time, intent distribution, and user satisfaction. With a modular architecture and efficient session management, the system ensures reliability, scalability, and ease of deployment. It demonstrates a clear advancement over traditional single-intent approaches by improving response efficiency, reducing processing delays, and enhancing the overall customer experience.

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