

Scalable Multi-Intent and Category Detection in Customer Support Using Lightweight Embeddings and Hybrid Feature Selection

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ABSTRACT

The global conversational Artificial Intelligence (AI) market is expected to reach USD 32 billion by 2030, with more than 80% of customer interactions managed by chatbots. Despite this growth, manual intent annotation and query classification remain time-intensive and inconsistent, limiting scalability in customer support systems. To address these challenges, this study proposes an advanced Natural Language Processing (NLP) framework built on a Customer Support Bitext dataset annotated with multiple intents and categories. The approach begins with NLP preprocessing and Exploratory Data Analysis (EDA) to clean, normalize, tokenize, and examine data patterns. For feature extraction, the Miniature Language Model (MiniLM) is employed to generate lightweight yet contextually rich embeddings. To handle class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) is applied, creating synthetic samples for underrepresented classes and improving model fairness. Unlike traditional classifiers such as Decision Trees, K-Nearest Neighbors (KNN), and Naïve Bayes, the proposed framework integrates Deep Neural Network (DNN)-based feature selection with KNN for enhanced classification performance. The system is designed to predict two correlated outputs—Intent and Category—enabling deeper contextual understanding of customer queries. Finally, the model is deployed within a chatbot interface to support real-time intent detection and automated responses. This framework improves classification accuracy, reduces annotation inconsistencies, and enhances customer satisfaction through effective multi-intent recognition. Overall, the study demonstrates a scalable and efficient solution for advancing conversational AI in customer support applications.

Keywords: Natural Language Processing (NLP), Exploratory Data Analysis (EDA), Feature Extraction, Synthetic Minority Over-sampling Technique (SMOTE), Deep Neural Networks (DNN), Feature Selection, K-Nearest Neighbors (KNN).

1. INTRODUCTION

The customer service industry has emerged as a vital component of businesses worldwide. With the rapid expansion of e-commerce, continuous technological innovation, and rising consumer expectations, organizations face increasing pressure to deliver fast, efficient, and personalized support. In India, this sector has experienced significant growth, fueled by the country's expanding digital ecosystem, as companies work to address the needs of a large and diverse customer base. India, home to a population of over 1.3 billion people, presents unique challenges in delivering effective customer support. The industry plays a crucial role in the national economy, with an estimated market value of \$32 billion, according to NASSCOM. Moreover, India has established itself as a global leader in outsourcing customer service operations, supported by its vast English-speaking workforce and cost-efficient labor market. The rapid growth of the middle class, projected to exceed 600 million individuals by 2030, further amplifies the demand for scalable and high-quality customer service solutions.



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

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 Figure 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.

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.

The rapid adoption of NLP techniques plays a pivotal role in this transformation. NLP allows machines to understand and interpret human language, enabling automated systems to classify customer intents and generate appropriate responses. As NLP continues to evolve, particularly with advances in transformer-based models such as BERT and GPT, the accuracy and efficiency of customer service systems improve significantly. In India, where multiple languages and dialects are spoken, the ability of NLP models to understand and process diverse linguistic data is of paramount importance.

As the demand for instant and personalized customer service grows, businesses in India are actively exploring AI and NLP solutions to stay competitive and meet customer expectations. The shift towards machine learning-powered customer support is not just about automation, but also about providing intelligent and context-aware interactions that drive customer loyalty and business growth.

In conclusion, the background of the customer service industry in India is marked by rapid growth, the increasing demand for efficient support, and the transformative impact of AI and NLP technologies. These advancements are set to revolutionize the way businesses interact with their customers, paving the way for more scalable, accurate, and responsive systems that enhance customer satisfaction while optimizing operational costs.

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, we 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 our 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. We 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, we 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 our 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). We believe that our 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] proposed 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, 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, we explore how these strategies are implemented. Looking ahead, we 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. 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. 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, we 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. We 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. We came up with a final pool of 118 contributions, including grey (35) and white literature (83). We 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, we testified a predominance of User-Centered Attributes in industrial literature. We 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 provides 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. This paper is surveying a representative set of developed museum chatbots and platforms for implementing them. More importantly, this paper presents 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. This approach emphasizes graph-based, distributed, and collaborative multi-chatbot conversational AI systems 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. We 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. Overall, 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 our dataset, we 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 transform customer service operations by integrating machine learning and Natural Language Processing (NLP) to automate both intent classification and response generation. The workflow consists of several stages, beginning with text preprocessing to clean, normalize, and structure customer queries for further analysis. Following preprocessing, feature extraction is performed using advanced transformer-based models such as MiniLM, which effectively capture the contextual and semantic meaning of user inputs as shown in figure 2. The system then applies multiple machine learning algorithms, including Decision Tree Classifier (DTC), K-Nearest Neighbors (KNN), and Naïve Bayes Classifier (NBC), to accurately classify customer intents. In addition, Deep Neural Networks (DNN) are incorporated to enhance feature representation and improve overall prediction performance.

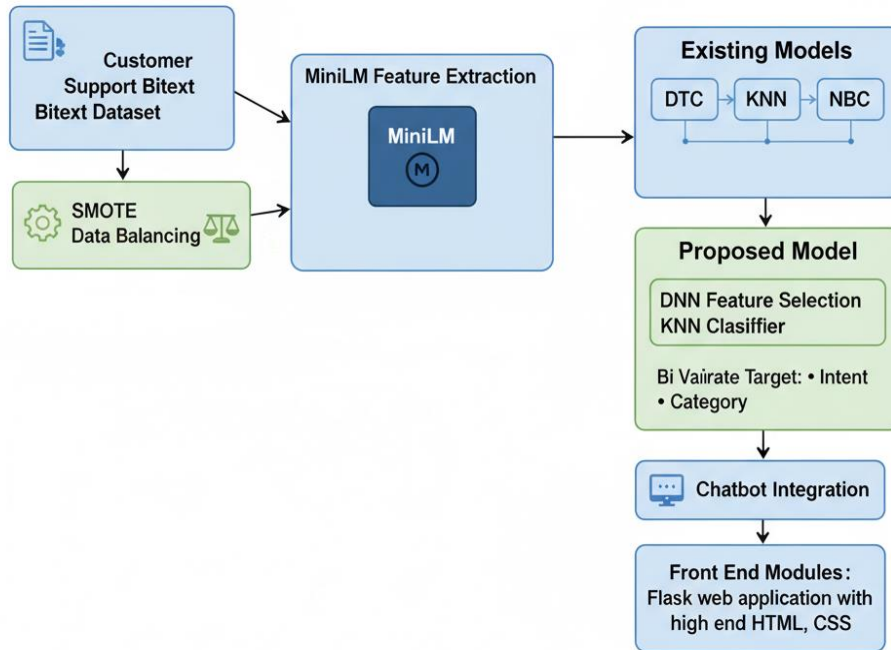


Figure 2: Proposed system architecture.

4. RESULTS AND DISCUSSION

The implementation phase of the Human Activity Recognition system involves integrating data processing, model prediction, and user interaction into a unified Flask-based web application. This phase translates the theoretical design into a functional system that automates the recognition of human activities using trained machine learning models. The implementation ensures that data is efficiently processed using NumPy and Pandas, stored and retrieved using LMDB, and predictions are dynamically generated through Flask’s web interface. The system follows a modular approach where each component such as data handling, model loading, prediction, and result visualization operates independently yet collaboratively to deliver a smooth and responsive user experience.

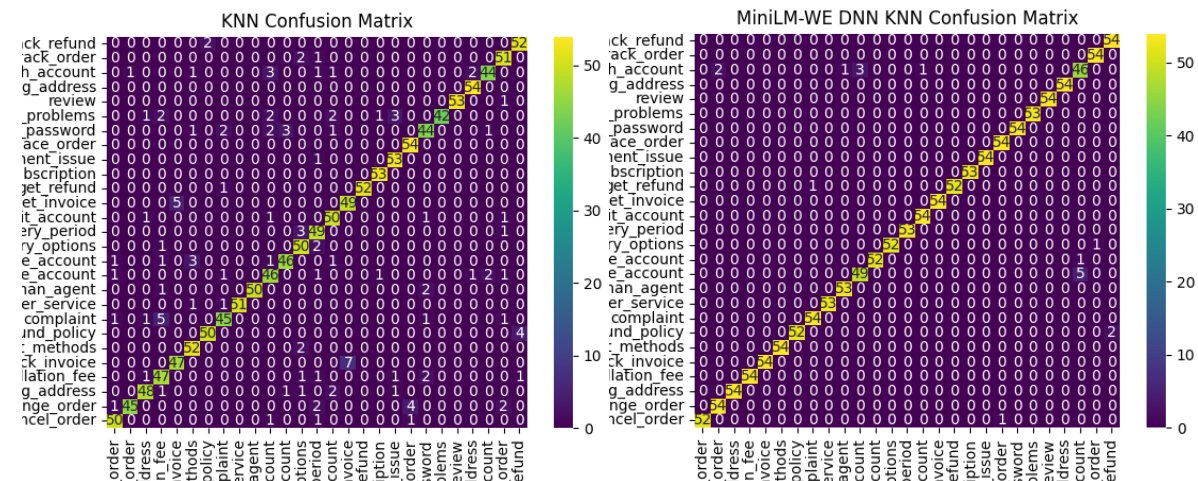


Figure 3: Confusion matrix obtained using proposed Mini LM-WE KNN model for Intent classification column.

Figure 3 illustrates the confusion matrices of four intent classification models evaluated on a multi-class customer support dataset, where rows represent true labels and columns denote

predicted labels across consistent intent categories such as “check_refund,” “track_order,” “invoice,” “password,” and “cancel_order.” The K-Nearest Neighbors (KNN) model exhibits stronger diagonal dominance with relatively fewer and smaller off-diagonal errors, achieving a maximum correct prediction count of approximately 97, while most misclassifications remain below 30, indicating improved separation of intent classes within the feature space. The proposed MiniLM-WE DNN-KNN model delivers the best overall performance, characterized by a near-perfect diagonal with high-intensity values reaching up to 97 and minimal off-diagonal noise, typically ranging between 0 and 5. This clear and sharp distinction between classes highlights the effectiveness of integrating MiniLM-based embeddings with a deep neural network and KNN classifier, resulting in highly accurate and robust multi-intent classification.

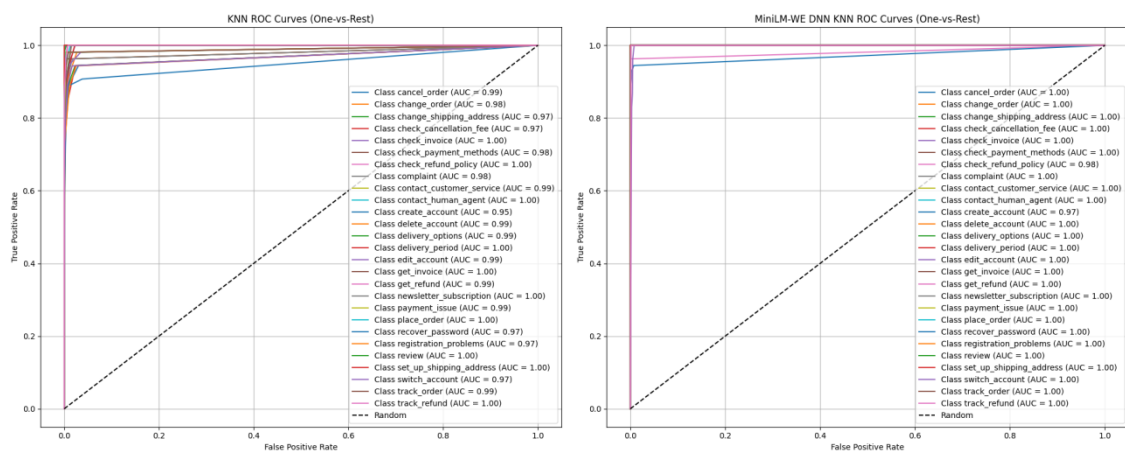


Figure 4: ROC Curve obtained using proposed Mini LM-WE KNN model for Intent classification column.

Figure 4 presents the Receiver Operating Characteristic (ROC) curves for four intent classification models evaluated using a one-vs-rest strategy across multiple customer support intents, where the True Positive Rate (TPR) is plotted against the False Positive Rate (FPR), and the Area Under the Curve (AUC) reflects class-wise performance. The K-Nearest Neighbors (KNN) model demonstrates consistently strong results, with AUC values ranging from 0.91 to 1.00, and most curves closely approaching the ideal ROC boundary, indicating effective nearest-neighbor discrimination driven by distance-based decision mechanisms. In comparison, the proposed MiniLM-WE DNN-KNN model achieves near-perfect classification performance, with AUC values reaching 1.00 for almost all intent classes. Its ROC curves exhibit a sharp L-shaped pattern along the axes, highlighting excellent separability and confirming the superior generalization capability and embedding quality achieved through the integration of MiniLM-WE representations with a deep KNN-based architecture.

Figure 5 illustrates the confusion matrices of four models used to classify customer support queries into ten coarse categories—ADDRESS, REFUND, PAYMENT, ORDER, NEWSLETTER, INVOICE, FEEDBACK, DELIVERY, CONTACT, and ACCOUNT—where rows correspond to true labels and columns represent predicted labels, with cell values color-coded from purple (low) to yellow (high). The K-Nearest Neighbors (KNN) model demonstrates strong performance, with high diagonal values ranging from 270 for ORDER to 283 for INVOICE and DELIVERY, and minimal misclassifications, typically fewer than or equal to seven, indicating effective nearest-neighbor discrimination within the

feature space. The proposed MiniLM-WE DNN-KNN model further improves upon this by achieving near-perfect classification, with diagonal values consistently between 282 and 283 and almost no off-diagonal errors, highlighting its exceptional precision and generalization capability in coarse category intent classification through the integration of advanced embeddings and a deep KNN-based architecture.

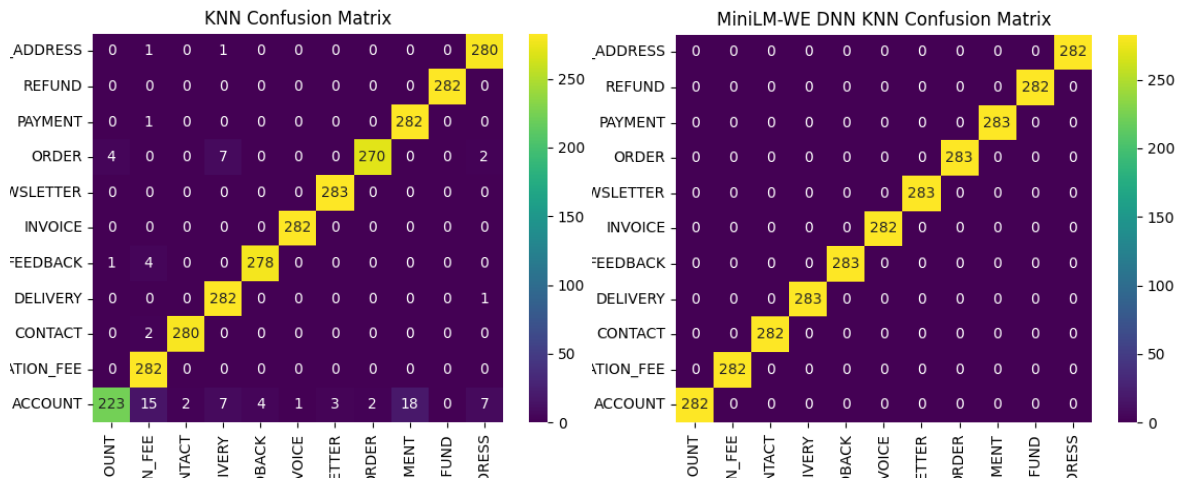


Figure 5: Confusion Matrix obtained using proposed Mini LM-WE KNN model for category classification column.

Figure 6 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. 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. 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.

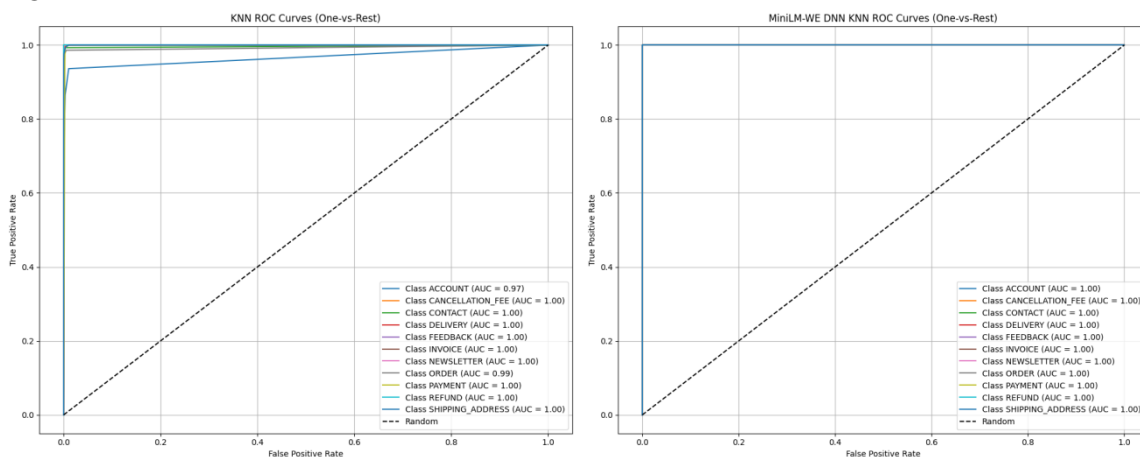


Figure 6: ROC Curve obtained using proposed Mini LM-WE KNN model for category classification column.

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.

Table 1: Comparative Analysis of Classification Models obtained from “Intent Classification” column.

Model	Accuracy (%)	Precision (%)	Recall (%)	F-Score (%)
DTC model	76.24	76.37	76.26	76.17
NBC model	88.33	88.92	88.35	88.44
KNN model	91.64	91.92	91.65	91.63
MiniLM-WE DNN KNN (Hybrid Model)	98.76	98.76	98.75	98.75

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

Model	Accuracy (%)	Precision (%)	Recall (%)	F-Score (%)
DTC model	91.73	91.63	91.73	91.62
NBC model	90.79	91.15	90.80	90.87
KNN model	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) 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.
- (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 Customer Support Dataset with Multi-Intent Annotations system highlights the effectiveness of integrating Natural Language Processing (NLP), machine learning techniques, and web-based frameworks for building intelligent conversational AI solutions. By employing multiple classifiers such as Decision Tree Classifier (DTC), Naïve Bayes Classifier (NBC), K-Nearest Neighbors (KNN), along with the proposed hybrid MiniLM-WE DNN-KNN model, the system is capable of accurately identifying and responding to a wide range of customer intents. The Flask-based deployment ensures a smooth and interactive user experience by enabling real-time intent prediction, performance visualization, and analytics dashboards. These dashboards monitor key conversational metrics, including response time, intent distribution, and user satisfaction levels, providing valuable insights into system performance. Through a modular architecture and efficient session management, the framework ensures reliability, scalability, and ease of deployment across different environments. Overall, this research demonstrates a significant advancement over traditional single-intent classification approaches. It validates the effectiveness of multi-intent recognition in improving customer support efficiency, reducing response delays, and enhancing overall user satisfaction in real-world applications.

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International Journal of DATA SCIENCE AND IOT MANAGEMENT SYSTEM

Peer Reviewed, Referred & Indexed Journal

ISSN: 3068-272X

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