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GENAI – VOICE OF CUSTOMER

[1]Abhishek Patil , [2]Akshay Bramhankar, [3]Parimal Pawar, [4]Parth Nigade, [5]Prof. Tejal H. Patil.

[1][2][3][4] Student, Department Of Information Technology, Sinhgad College Of Engineering, Pune.

[5] Professor, Department Of Information Technology, Sinhgad College Of Engineering, Pune.

Abstract: This project develops a Generative AI (GenAI) system to automate and enhance customer feedback management. By integrating natural language generation and sentiment analysis, the system categorizes feedback, routes concerns to relevant departments, and provides personalized responses in real time. It handles mixed sentiments and multi-topic feedback more effectively than traditional methods, reducing customer service workload and improving response times. The system flags complex issues requiring human intervention, ensuring high-quality responses. Future improvements aim to enhance the handling of more complex feedback and further personalize responses.

Keywords - Generative AI, customer feedback, sentiment analysis, automation, personalized responses.

I. INTRODUCTION

In today's increasingly competitive business environment, the efficient management of customer feedback has become critical for maintaining high levels of customer satisfaction and loyalty, as well as ensuring long-term success. As businesses interact with customers across a multitude of platforms, the volume and complexity of feedback they receive have grown exponentially, posing significant challenges to traditional feedback management systems. These conventional methods, often reliant on manual processes, are not only labor-intensive but also fail to capture the full range of nuances present in modern customer interactions, such as multi-topic messages and mixed emotional sentiments. As a result, companies frequently miss opportunities to respond promptly and effectively to customer needs, potentially damaging their relationships and reputation. This challenge has driven the need for more advanced, automated systems capable of handling vast amounts of feedback with greater accuracy, speed, and contextual understanding. In response to these challenges, the integration of Generative AI (GenAI) into customer feedback systems offers a transformative solution, providing businesses with the ability to automate crucial aspects of feedback analysis, categorization, and response generation. Unlike traditional Natural Language Processing (NLP) techniques, which primarily focus on sentiment analysis or basic categorization, GenAI enables a more sophisticated approach that can interpret complex, multi-layered feedback in real-time. By leveraging GenAI, businesses can efficiently analyze feedback, detect mixed sentiments within individual messages, and even generate personalized responses tailored to the customer's specific concerns, all while ensuring these responses are routed to the appropriate departments for timely action. This automation not only alleviates the burden on human resources but also significantly reduces the time it takes for businesses to respond to customer feedback, fostering stronger customer relationships and improving overall satisfaction. Furthermore, the scalable nature of AI-driven systems means that as the volume of customer feedback increases, businesses can continue to process and respond to these inputs without compromising speed or quality, making it an ideal solution for organizations experiencing rapid growth or fluctuating demands. By continually learning from new data, the AI system becomes increasingly adept at interpreting feedback with greater precision, ensuring that businesses remain responsive and adaptive in dynamic markets. Ultimately, the integration of GenAI into customer feedback management represents a significant advancement over traditional methods, combining efficiency, scalability, and personalization to create a more intelligent and customer-centric feedback system. This project not only builds upon existing NLP techniques but also introduces novel functionalities that make feedback management more responsive and capable of driving better business outcomes. In the fast-paced digital economy, where customer expectations for timely and accurate interactions are higher than ever, this AI-powered system offers businesses a vital tool for maintaining competitive advantage, enhancing operational efficiency, and fostering deeper customer engagement, positioning them for sustained success in an ever-evolving marketplace.

1.1 Motivation
In today's highly competitive business environment, customer feedback is critical for improving products and services. Companies need efficient methods to manage and respond to this feedback in real time. Generative AI (GenAI) offers an advanced solution to automate this process, allowing businesses to parse, interpret, and respond to customer input effectively. By utilizing GenAI, companies can provide personalized responses, route feedback to the appropriate departments, and take timely action to address concerns, improving overall customer satisfaction.

1.2 Problem Definition
Traditional Natural Language Processing (NLP) systems struggle to handle complex customer feedback, especially when it includes multiple topics or mixed sentiments (both positive and negative). Existing methods fail to categorize such feedback accurately, leading to inefficiencies in managing customer concerns. The challenge lies in developing a system that can not only parse feedback comprehensively but also identify the appropriate action, department, or response required. A GenAI-based system aims to overcome these limitations by effectively analyzing and automating feedback management, reducing the need for human intervention while maintaining quality responses.

II. LITERATURE SURVEY

Kuldeep Singh Kaswan et al [1]. (2023). Generative AI: A Review on Models and Applications. Kaswan and colleagues provided an extensive review of generative artificial intelligence models and their applications across diverse domains, with an emphasis on Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and other architectures such as flow-based and hybrid models. The study examined the foundational aspects, training methodologies, optimization techniques, and evaluation metrics, including the Inception Score and Fréchet Inception Distance. It highlighted the transformative potential of generative AI in fields like image synthesis, text generation, music composition, and drug discovery. The authors also discussed challenges such as mode collapse, data quality, and ethical considerations, including bias in model outputs. This review contributes to the literature by exploring the evolving landscape of generative AI and providing insights into future advancements like few-shot learning and interpretability mechanisms to enhance model robustness and applicability.
Sri Lalitha et al [2]. (2022). Analysis of Customer Reviews Using Deep Neural Networks. This study, led by Sri Lalitha and colleagues, focused on sentiment analysis of customer reviews using deep learning techniques, specifically targeting reviews for electronics and clothing on Amazon. The goal was to classify reviews as positive, negative, or neutral sentiments. The research employed Convolutional Neural Networks (CNNs) for text classification with n-gram retention and Recurrent Neural Networks (RNNs) to capture sequential dependencies for better text comprehension. Data preprocessing involved tokenization and oversampling to handle dataset imbalances. RNNs demonstrated superior performance over CNNs in precision and sentiment classification, emphasizing deep learning's impact on capturing customer perspectives and product sentiment. The study suggested further exploration of multi-model inputs and integrating big data technologies for scalability.
Pankaj et al [3]. (2019). Sentiment Analysis on Customer Feedback Data: Amazon Product Reviews. Proceedings of the 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (Com-IT-Con). Pankaj's study aimed to classify Amazon product reviews into positive, negative, or neutral categories to help businesses assess customer satisfaction and improve product quality. Using over 500 reviews from categories like Mobiles, Computers, and Electronics, the research demonstrated efficient methods for handling and interpreting large volumes of user data. Techniques included Part-of-Speech (POS) Tagging for filtering non-subjective language, Sentiment Polarity Categorization, and a Max-Entropy POS

Tagger for refining semantic understanding, all contributing to effective sentiment categorization and insights extraction. This work highlighted structured sentiment analysis' value in understanding customer preferences and enhancing product strategies.

Cheonsu Jeong et al [4]. (2023). A Study on the Implementation of Generative AI Services Using an Enterprise Data-Based LLM Application Architecture. Advances in Artificial Intelligence and Machine Learning. This paper by Jeong and colleagues explores the use of generative AI in enterprise environments, proposing a Large Language Model (LLM) architecture designed for enterprise data integration. The study addresses issues such as data scarcity and hallucination by developing a Retrieval-Augmented Generation (RAG) model, which merges information retrieval with generative capabilities to enhance AI output reliability and contextual relevance. Techniques such as fine-tuning and embedding algorithms were used to manage large datasets efficiently, while vectorized databases facilitated quick, similarity-based data retrieval. This approach demonstrates how RAG integration improves AI-generated responses' quality and applicability in corporate contexts.

Philipp Reinhard et al [5]. (2024). Generative AI in Customer Support Services: A Framework for Augmenting the Routines of Frontline Service Employees. Proceedings of the Hawaii International Conference on System Sciences. Reinhard and colleagues propose a framework for embedding generative AI into customer support services to enhance frontline service employees' (FSE) routines. The study identifies roles where AI can augment workflows using a multi-method approach, including literature reviews, interviews, and workshops with IT support agents and AI experts. The framework emphasizes capabilities like AI-Mediated Communication (AI-MC) to improve interactions, Collaborative Writing Support for documentation, and Decision Support Systems for complex decisions. This model contributes to understanding generative AI's practical applications in customer service, aiming to reduce workload and increase customer satisfaction.

Lwin et al [6]. (2020). Feedback Analysis in Outcome-Based Education Using Machine Learning. Proceedings of the 2020 International Conference on Electrical Engineering/Electronics, Computer, Telecommunications, and Information Technology (ECTI-CON). Lwin and colleagues developed a feedback analysis system to assess university teaching and learning effectiveness, complementing rating scores with numerical and textual feedback. The study applied K-means clustering to categorize ratings into five levels (Excellent, Good, Neutral, Bad, and Worse) for supervised classification. Models such as Support Vector Machine (SVM), Logistic Regression, and Random Forest were used, with SVM demonstrating the highest precision. A Naïve Bayes classifier was utilized for textual sentiment classification following preprocessing steps like tokenization, normalization, and word density analysis. Evaluated using 10-fold cross-validation, the Naïve Bayes classifier proved effective, offering a comprehensive view of student feedback and actionable insights for educational quality improvement.

III. PROPOSED METHODOLOGY AND TECHNOLOGY

3.1 Retrieval-Augmented Generation (RAG)

RAG enhances the relevance and accuracy of responses in generative AI by combining traditional information retrieval with generation tasks. RAG begins by retrieving relevant documents or knowledge from a pre-established database or enterprise repository in response to a query. The AI model then uses this retrieved information to generate a response. This dual approach of retrieving and generating ensures that the response remains grounded in factual data, reducing the AI's tendency to "hallucinate," or generate plausible but inaccurate information. In Jeong's[3] study, RAG is used to integrate enterprise-specific data with generative AI capabilities. This is crucial in business settings where responses must be accurate and contextually relevant. By ensuring that generated responses are directly linked to real data, RAG enhances the trustworthiness and practical applicability of generative AI within corporate environments. This also addresses common issues in LLMs, such as data limitations, by continuously enriching AI output with enterprise-specific content, providing a more reliable AI service for end-users.

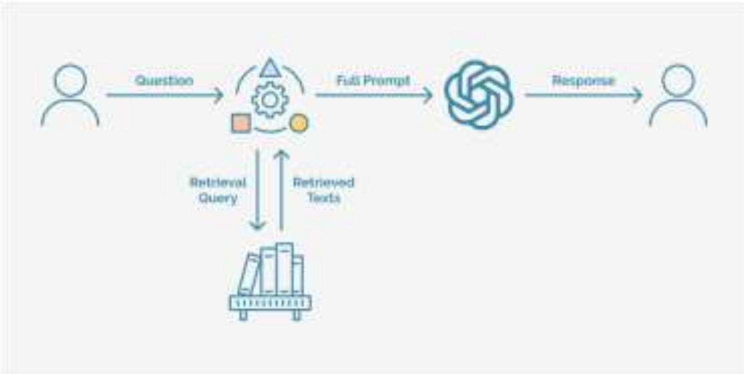

FIG NO.: 3.1 Retrieval-Augmented Generation (RAG)

3.2 Support Vector Machine (SVM)

SVM is employed for precise classification, especially useful in high-dimensional spaces, to categorize feedback ratings into predetermined classes. SVM works by finding the optimal hyperplane that separates data points belonging to different classes (in this case, feedback rating categories). It relies on margin maximization, which means it places the separating hyperplane as far as possible from the closest points of each class. SVM's support vectors (the data points closest to the hyperplane) ensure that even complex or overlapping data can be separated accurately. In the study by Lwin et al.[5], SVM was used to classify feedback ratings into categories (Excellent, Good, Neutral, Bad, Worse), which were initially clustered using K-means. By identifying distinct classes in the feedback data, SVM improves the interpretability of student feedback, giving universities a clearer view of how their programs are perceived. SVM's high precision in classification tasks provides reliable outputs, supporting educational institutions in analyzing and acting upon student feedback to enhance learning outcomes.

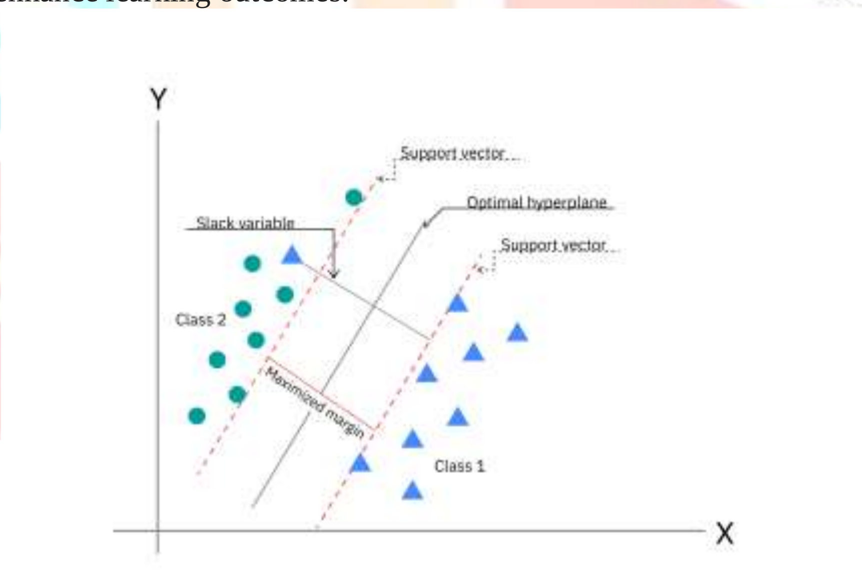

FIG NO.: 3.2 Support Vector Machine (SVM)

3.3 K-means Clustering

K-means clustering organizes unlabeled data (such as numerical feedback scores) into clusters to reveal patterns or categories. K-means is an unsupervised learning algorithm that iteratively assigns each data point to the nearest cluster center (centroid) and then recalculates the centroid's position based on the points in that cluster. This process repeats until convergence, producing clusters of data points that are similar within each cluster but different from points in other clusters. In Lwin et al[5].'s study, K-means was applied to organize rating scores from student feedback into five meaningful levels: Excellent, Good, Neutral, Bad, and Worse. This clustering step was foundational because it labeled the data for subsequent classification using supervised algorithms like SVM and Logistic Regression. By converting raw ratings into discrete categories, K-means allowed the researchers to better capture and interpret the nuances in feedback, enhancing the university's ability to assess teaching effectiveness comprehensively.

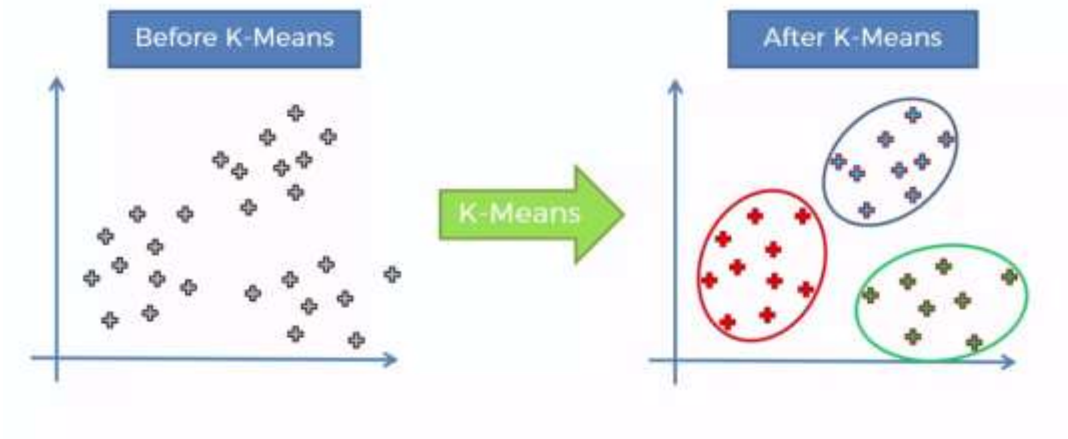

FIG NO.: 3.3 K-means Clustering

3.4 Naïve Bayes Classifier

The Naïve Bayes classifier provides efficient and interpretable sentiment analysis of textual comments, categorizing them as positive or negative. Naïve Bayes is a probabilistic classifier based on Bayes' theorem, assuming independence among features (words, in this case). The classifier calculates the probability of a text belonging to a specific class (positive or negative sentiment) based on the occurrence of words typically associated with that class. Despite the independence assumption, it performs well on text classification tasks by analyzing word frequencies. Lwin et al[5]. used the Naïve Bayes classifier to analyze and classify student feedback comments as positive or negative. After pre-processing steps like tokenization, normalization, and word density analysis, Naïve Bayes classified the textual feedback, providing a sentiment overview that complements the numerical rating scores. By combining both numeric and text analysis, the research could present a richer, more comprehensive understanding of student perceptions, which is critical for continuous educational improvement.

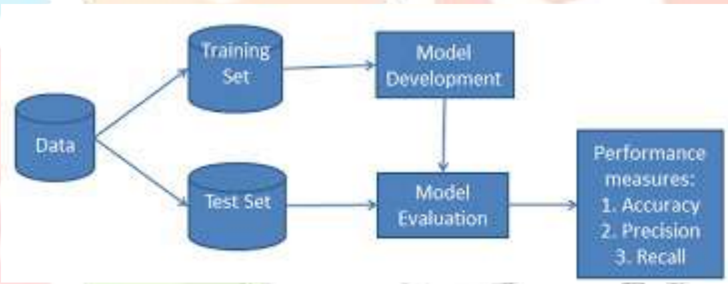

FIG NO.: 3.4 Naïve Bayes Classifier

3.5 Decision Support Systems (DSS)

Decision Support Systems provide recommendations to customer support employees, assisting in decision-making processes for issues such as escalation or complex problem-solving. DSS integrates data from past cases and interactions, using this historical information to inform real-time recommendations for employees. Based on predefined rules or machine learning models, DSS analyzes current cases, compares them with past instances, and provides suggested actions that optimize decision-making efficiency. Reinhard et al[4]. utilized DSS to support frontline service employees (FSEs) in customer support. By automating parts of the decision-making process, such as escalation and issue resolution, DSS aids employees in making consistent, data-driven decisions. This not only speeds up response times but also helps in maintaining service quality by reducing uncertainty and ensuring that decisions align with best practices. The system’s ability to provide real-time guidance is particularly valuable in complex cases, where informed decisions can directly impact customer satisfaction and service outcomes.

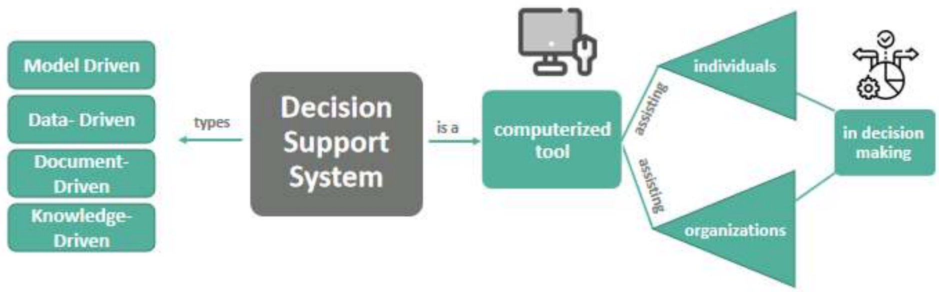

FIG NO.: 3.5 Decision Support Systems (DSS)

IV. CONCLUSION

In conclusion, this project successfully demonstrates the transformative potential of Generative AI (GenAI) in automating and enhancing customer feedback management systems. By leveraging advanced techniques such as sentiment analysis, Retrieval-Augmented Generation (RAG), Support Vector Machines (SVM), K-means clustering, and the Naïve Bayes classifier, the system adeptly categorizes complex customer feedback, effectively identifies mixed sentiments, and generates personalized responses in real time. The integration of these technologies not only streamlines the feedback management process but also significantly reduces the workload on customer service representatives, allowing them to focus on more complex issues that require human intervention. By flagging these intricate cases, the system ensures that customers receive high-quality responses, thereby fostering improved relationships and increasing overall customer satisfaction.

Moreover, this project addresses the shortcomings of traditional feedback management systems, which often struggle to process and interpret the nuances of customer feedback effectively. The GenAI system's capability to handle multi-topic feedback and provide timely, contextually relevant responses positions it as a crucial tool for businesses seeking to maintain competitive advantages in a fast-paced digital environment. Looking ahead, future improvements will focus on refining the handling of even more complex feedback scenarios and enhancing the personalization of responses. This ongoing evolution will ensure that the system continues to meet the dynamic needs of businesses and their customers, ultimately driving better outcomes in customer engagement and satisfaction. The findings and methodologies presented in this research not only contribute to the existing body of knowledge in the field of customer feedback management but also pave the way for further innovations in Generative AI applications across various industries.

V. REFERENCES

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