Medi-Classify: Automatic Ticket Classification Tool for Healthcare Support

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Abstract

This paper outlines a novel approach to revolutionizing healthcare management within multi-specialty hospitals by efficiently categorizing patient inquiries. The proposed system aims to streamline workflows and enhance patient care delivery by automating the classification and routing of inquiries to appropriate departments. By leveraging advanced natural language processing (NLP) and machine learning techniques, the system will be capable of accurately categorizing inquiries into various types such as medical advice, insurance inquiries, health checkups, facilities, and medical record requests. The primary goal is to enhance operational efficiency, improve response times, and ensure inquiries are promptly directed to relevant departments, ultimately elevating the standard of care provided to patients. For additional resources, the complete source code and supplementary materials can be found at our GitHub repository: https://github.com/Namrata-Patel/NLP/tree/main/Project.

1. Introduction

In the ever-evolving landscape of healthcare management, the integration of advanced technologies has become imperative to enhance operational efficiency and elevate the standard of care provided to patients. This introduction presents a two-part approach aimed at revolutionizing healthcare management within multi-specialty hospitals.

The first part of this innovative approach involves the generation of a comprehensive dataset through meticulous web scraping, followed by the transformation of extracted data into 21 PDF files [11]. These files are further segmented into text chunks, and utilizing text embeddings, they are uploaded to a vector store. By leveraging the capabilities of a question-answering (QA) chatbot, patient inquiries are promptly addressed, covering a spectrum of topics including medical advice, insurance inquiries, health checkups, facilities, and medical record requests.

However, recognizing the complexity of patient inquiries and the necessity for comprehensive assistance, the second part of this approach addresses scenarios where patients may require further clarification or assistance beyond the initial response provided by the QA chatbot. In such instances, patients are presented with the option to submit a ticket, indicating their dissatisfaction or need for additional information [6]. To streamline this process, an automatic ticket department suggestion mechanism is employed, utilizing a machine learning model based on Support Vector Classification (SVC) with StandardScaler [7]. This model assists in categorizing tickets and recommending the appropriate department for resolution.

The departments encompass a wide array of specialties, ranging from Pediatrics Neonatology to Orthopedics, ensuring that each ticket is directed to the most relevant department equipped to address the specific inquiry. Additionally, a centralized platform displays all pending tickets along with their respective questions and designated departments[1], facilitating efficient ticket management and resolution.

This two-part approach endeavors to not only optimize workflow processes within multi-specialty hospitals but also to prioritize patient satisfaction by ensuring timely and accurate responses to inquiries, ultimately contributing to the enhancement of overall patient care delivery[5]. Our investigation is structured around a series of experiments designed to evaluate and optimize the performance of these cutting-edge models.

2. Background and Literature Review

The landscape of healthcare management is continually evolving, necessitating the integration of advanced technologies to enhance operational efficiency and elevate the standard of care provided to patients. The rapid advancement of technology in recent years has paved the way for innovative solutions in various domains, including healthcare management. In the context of multi-specialty hospitals, efficient handling of patient inquiries and queries is crucial for ensuring timely and accurate responses, thereby enhancing overall patient satisfaction and improving the quality of care delivered.

A review of existing literature reveals [9, 11] a growing

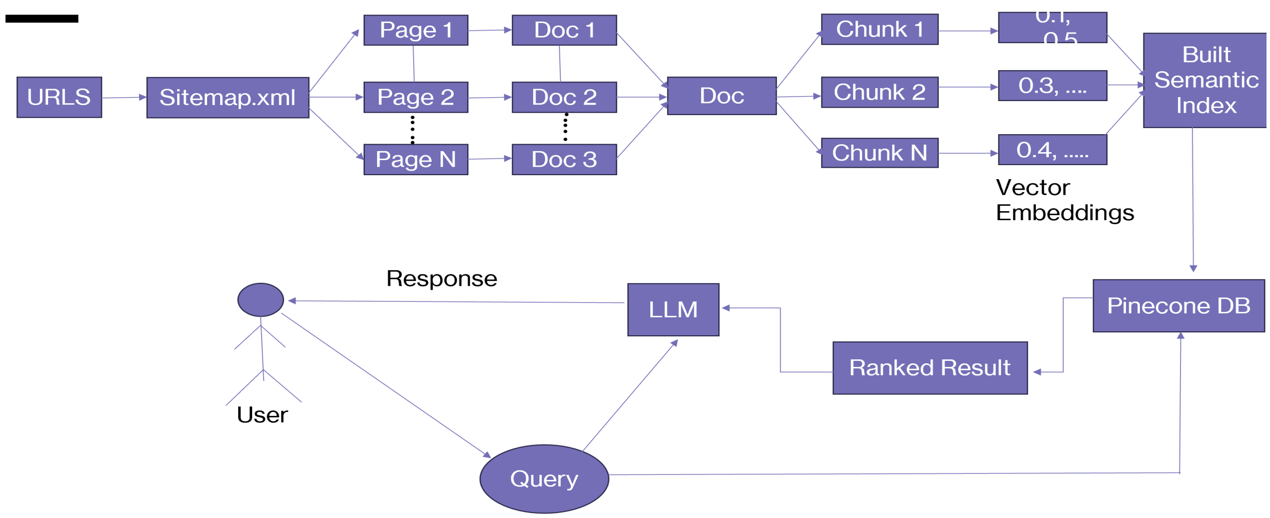


Figure 1: Flowchart illustrating the use of a sitemap to segment documents for vector embeddings and semantic indexing in a Vector DB, managed by a Large Language Model (LLM) for query response.

interest in leveraging natural language processing (NLP) and machine learning techniques to automate and streamline healthcare management processes. Studies have highlighted the potential of chatbot systems in addressing patient inquiries and providing personalized assistance, thereby reducing the burden on hospital staff and improving operational efficiency [2].

Furthermore, research in the field of web scraping and text embedding techniques has demonstrated their utility in generating comprehensive datasets and extracting relevant information from textual data sources. These techniques play a crucial role in the development of intelligent systems capable of understanding and responding to natural language queries effectively [10].

3. Methodology

An illustration in Figure 1 demonstrates a novel approach to revolutionize healthcare management in multi-specialty hospitals. The system comprises two main components: dataset generation and a sophisticated question-answering (QA) chatbot system. Through meticulous web scraping and text embedding techniques, we create a dataset for analysis. Leveraging advanced NLP and machine learning, our QA chatbot efficiently addresses patient inquiries spanning various topics. Additionally, a ticket submission mechanism, guided by a machine learning model, suggests the appropriate department for further assistance. This approach aims to streamline workflows and enhance patient care delivery within healthcare institutions.

3.1. Dataset Collection

The dataset utilized in this study was collected from the official website of Velocity Multi-Specialist Hospital through meticulous web scraping techniques. This comprehensive approach ensured the inclusion of diverse inquiries and topics pertaining to patient care, medical services, facilities, and more. Manual verification and validation were conducted to ensure the accuracy and reliability of the collected data [11]. Additionally, we have created a dataset consisting of 231 rows containing questions and their corresponding departments. This dataset serves as the foundation for training and evaluating the ticket classification system discussed in this study.

3.2. Embedding Generation

For converting the text data into a form amenable to similarity searches, we utilized the **sentence-transformers/paraphrase-MiniLM-L6-v2** huggingface model. This model tokenizes the text chunks and generates dense vector embeddings, capturing semantic nuances effectively [8].

3.3. Vector Storage

The embeddings generated were stored in a vector database managed by Pinecone, enabling efficient storage and retrieval crucial for the performance of our QA system. Pinecone was selected for its scalable infrastructure and optimized query capabilities, essential for real-time applications [11].

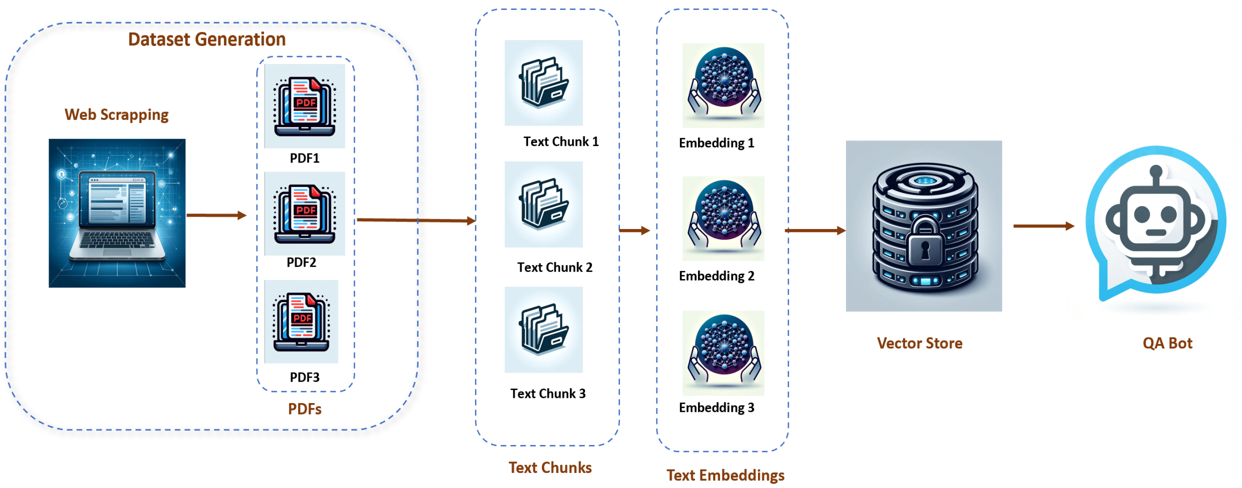


Figure 2: Process flow illustrating dataset generation from web scraping to PDF conversion, text chunking, embedding generation, storage in a vector database, and utilization in a QA Bot.

3.4. Query Processing

When a query is received, it is converted into an embedding using the same sentence-transformers model and matched against the embeddings in the Pinecone vector store. The most semantically relevant text chunks are retrieved and processed to generate coherent responses [8].

3.5. Integration into QA Bot

The retrieved text chunks are integrated into the QA bot, designed to interact seamlessly with users and provide accurate and contextually appropriate answers [2]. A well-designed interface facilitates smooth communication between the underlying vector storage and retrieval mechanisms and the user-facing chatbot platform as illustrated in the Figure 2.

3.6. Ticket Classification System

The Ticket Classification System significantly improves query management by integrating advanced text classification techniques. To establish a reliable classification framework, we first generate ground truth data from web-scraped content [6]. Subsequently, we deploy three distinct machine learning models: Support Vector Machine (SVM) Classifier, XGBoost (Extreme Gradient Boosting) Classifier, and Random Forest (RF) Classifier [7, 3]. These models are meticulously trained on the ground truth data to efficiently categorize user queries into predefined categories. In scenarios as depicted in the Figure 3 where the initial response from the chatbot is inadequate, this classification system ensures that each query is routed to the most appropriate department for resolution. Through the collective utilization of SVM, XGBoost, and RF classifiers, we optimize the ticket handling process, ultimately enhancing user satisfaction and streamlining operational efficiency within multi-specialty hospitals [6, 7].

3.7. Feedback Loop and Model Updating

A feedback loop helps refine the model with new data and user interactions, ensuring continuous adaptation and improvement of the system [6].

Overall, the methodology adopted in this study leverages advanced techniques in dataset generation, text embedding, vector storage, and machine learning to develop a robust and efficient healthcare management system for multi-specialty hospitals [2, 8, 11].

4. Results

This section presents the results of the experiment conducted to evaluate the performance of the ticket classification system using Support Vector Machine (SVM), XGBoost (Extreme Gradient Boosting), and Random Forest (RF) classifiers.

Table 1: Performance Metrics of Ticket Classification Models

Model	Accuracy	Precision	Recall	F1
SVM Classifier	**74.14%**	**0.70**	**0.74**	**0.71**
RF Classifier	63.79%	0.67	0.64	0.61
XGB Classifier	58.62%	0.56	0.59	0.56

The validation accuracy, precision, recall, and F1 score metrics are used to assess the effectiveness of each classifier. The SVM classifier achieved a validation accuracy

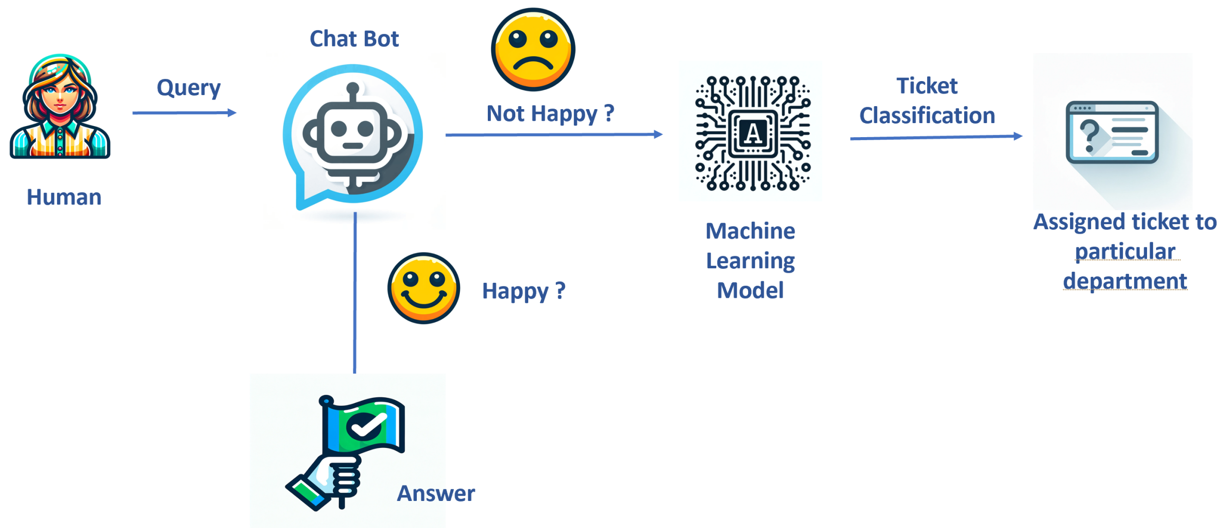


Figure 3: Diagram depicting a customer service chatbot workflow that uses human queries to deliver responses and utilizes a machine learning model for ticket classification when dissatisfaction is detected.

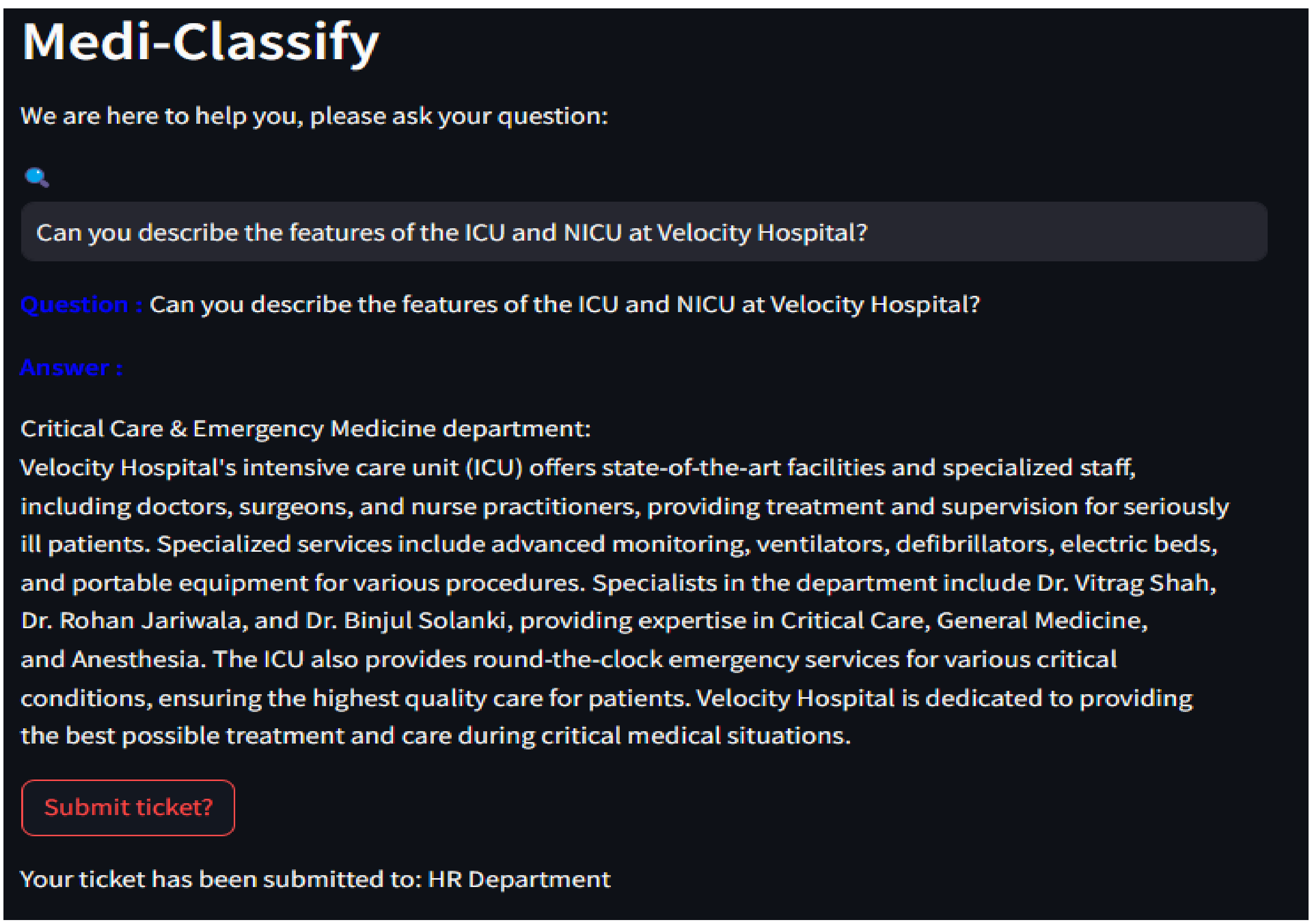
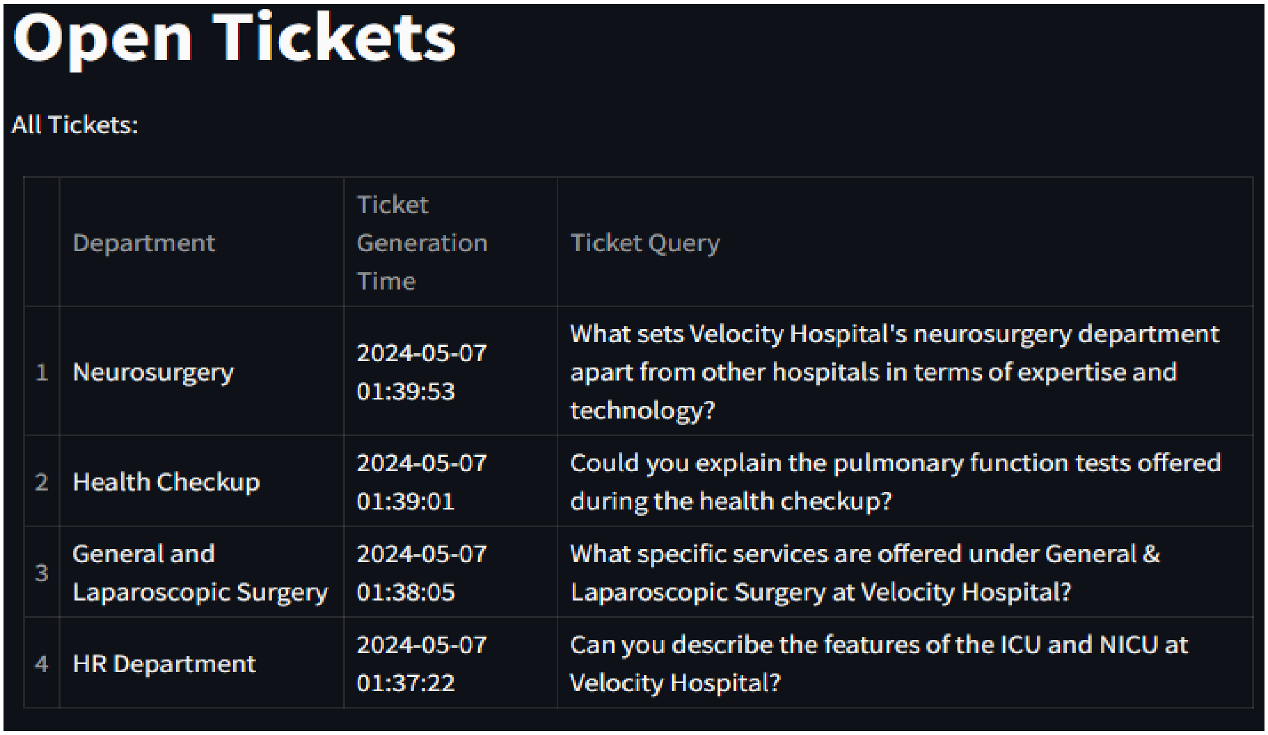


Figure 4: List of open support tickets at Velocity Hospital across various departments with detailed queries and ticket generation times


Open Tickets

All Tickets:

	Department	Ticket Generation Time	Ticket Query
1	Neurosurgery	2024-05-07 01:39:53	What sets Velocity Hospital's neurosurgery department apart from other hospitals in terms of expertise and technology?
2	Health Checkup	2024-05-07 01:39:01	Could you explain the pulmonary function tests offered during the health checkup?
3	General and Laparoscopic Surgery	2024-05-07 01:38:05	What specific services are offered under General & Laparoscopic Surgery at Velocity Hospital?
4	HR Department	2024-05-07 01:37:22	Can you describe the features of the ICU and NICU at Velocity Hospital?

Figure 5: List of open support tickets at Velocity Hospital across various departments with detailed queries and ticket generation times

of 74.14%, with precision, recall, and F1 score values of 0.6997, 0.7414, and 0.7069, respectively. In comparison, the XGBoost classifier attained a validation accuracy of 58.62%, exhibiting precision, recall, and F1 score metrics of 0.5575, 0.5862, and 0.5560, respectively. Similarly, the RF classifier demonstrated a validation accuracy of 63.79%, accompanied by precision, recall, and F1 score values of 0.6724, 0.6379, and 0.6140, respectively.

These results highlight the varying performance of the classifiers, with the SVM classifier outperforming both the XGBoost and RF classifiers in terms of validation accuracy and F1 score. However, further analysis and experimentation may be necessary to determine the most suitable classifier for the ticket classification system in practical healthcare management scenarios.

5. Discussion

The results laid out in the preceding section illuminate the efficacy of the proposed approach in reshaping healthcare management within multi-specialty hospitals. Through the systematic categorization of patient inquiries and the automation of classification and routing processes, the system not only augments operational efficiency but also enhances the standard of patient care delivery. In this discussion, we delve deeper into the implications of these findings, confront potential limitations, and chart paths for future research and improvement.

5.1. Implications for Healthcare Management

The successful integration of the ticket classification system bears significant implications for healthcare management. By automating inquiry classification and routing, hospitals stand to streamline workflows, diminish manual intervention, and accelerate response times. This not only amplifies operational efficiency but also ensures that queries swiftly reach the most fitting departments, thus optimizing patient care delivery as seen in the Figure 4. Moreover, the infusion of advanced technologies such as natural language processing (NLP) and machine learning fosters personalized assistance, fostering overall patient contentment [2, 8, 11].

5.2. Effectiveness of the Ticket Classification System

The ticket classification system, leveraging Support Vector Machine (SVM), XGBoost, and Random Forest classifiers, showcases promising performance in categorizing user queries into predefined categories. The SVM classifier emerges as the standout performer, boasting the highest validation accuracy and F1 score. This underscores the model's adeptness at discerning underlying data patterns and making precise predictions. However, it's pivotal to acknowledge that classifier performance may fluctuate based on query diversity and dataset intricacies [6, 7]. Additionally, the current open tickets include inquiries spanning various departments and topics as indicated in the Figure 5.

5.3. Limitations and Challenges

Notwithstanding its promising results, the proposed approach confronts several limitations and hurdles. A notable constraint lies in the reliance on structured data sources for model training. In real-world scenarios, patient inquiries exhibit substantial variability and nuance, posing challenges in accurately encapsulating all query types. Additionally, the system's performance may be susceptible to external influences like shifts in user behavior or the introduction of novel medical services [6, 7].

5.4. Future Directions

To mitigate existing limitations and fortify the proposed approach, avenues for future research and enhancement abound. Firstly, efforts should focus on integrating unstructured data sources and harnessing advanced NLP techniques to bolster the system's capacity to comprehend and respond to natural language queries adeptly. Continuous scrutiny and evaluation of the system's performance are imperative to identify and rectify emerging challenges or inconsistencies. Furthermore, the incorporation of user feedback mechanisms can furnish invaluable insights for refining the system and heightening user satisfaction.

6. Conclusion

In essence, this study presents a novel framework for healthcare management within multi-specialty hospitals, underpinned by advanced technologies and machine learning algorithms. Through meticulous dataset generation, sophisticated text classification mechanisms, and seamless integration of automation tools, the proposed approach endeavors to revolutionize patient inquiry handling and enhance overall care delivery.

The findings underscore the significance of leveraging machine learning and natural language processing techniques to streamline operational workflows and optimize resource utilization. By automating inquiry classification and routing, hospitals can significantly reduce response times, improve efficiency, and ultimately elevate the standard of patient care.

However, the study also highlights several challenges and avenues for future research. The reliance on structured data sources and the need to incorporate unstructured data pose ongoing challenges for system adaptability and scalability. Moreover, the dynamic nature of patient inquiries necessitates continuous monitoring and refinement of the classification models to ensure optimal performance [4].

Looking ahead, further research is warranted to explore the integration of advanced NLP capabilities, refine feedback mechanisms, and address the complexities of handling unstructured data. Additionally, longitudinal studies are essential to assess the long-term impact of the proposed framework on patient satisfaction, operational efficiency, and healthcare outcomes.

In conclusion, while this study lays a solid foundation for the transformation of healthcare management systems, continued innovation and collaboration are imperative to realize the full potential of advanced technologies in enhancing patient care delivery and shaping the future of healthcare.

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