

##### TRANSFORMING RAILMADAD SYSTEM:

##### AN AI-DRIVEN APPROACH TO COMPLAINT RESOLUTION

##### A PROJECT REPORT

###### ***Submitted by***

**KISHORE K (927621BEC095)**

**MOHAMED ANAS S (927621BEC121)**

**MOHANKUMAR R (927621BEC124)**

**BALAKUMAR A (927621BEC302)**

***in partial fulfillment for the award of the degree***

***of***

**BACHELOR OF ENGINEERING**

in

# ELECTRONICS AND COMMUNICATION ENGINEERING

M.KUMARASAMY COLLEGE OF ENGINEERING, KARUR

##### ANNA UNIVERSITY: CHENNAI 600 025

**APRIL 2025**

**M.KUMARASAMY COLLEGE OF ENGINEERING, KARUR**

**BONAFIDE CERTIFICATE**

##### Certified that this project report “TRANSFORMING RAILMADAD SYSTEM: AN AI-DRIVEN APPROACH TO COMPLAINT RESOLUTION” is the bonafide work of “KISHORE K (927621BEC095), MOHAMED ANAS S (927621BEC121), MOHANKUMAR R (927621BEC124), BALAKUMAR A (927621BEC0302)” who carried out the project work under my supervision in the academic year 2024-2025.

|  |  |
| --- | --- |
| **SIGNATURE** | **SIGNATURE** |
| **Dr.A.KAVITHA, M.E.,Ph.D.,** | **Mr.S.MOHANRAJ, M.E.,(Ph.D).,** |
| **HEAD OF THE DEPARTMENT** Professor,  Department of Electronics and Communication Engineering,  M.Kumarasamy College of Engineering,  Thalavapalayam, Karur-639113 | **SUPERVISOR**  Assistant Professor**,**  Department of Electronics and Communication Engineering,  M.Kumarasamy College of Engineering,  Thalavapalayam, Karur-639113 |

This project report has been submitted for the **18ECP107L - Project Work** Viva Voce Examination held at M.Kumarasamy College of Engineering, Karur on \_\_\_\_\_\_\_\_\_\_\_\_\_\_.

**INTERNAL EXAMINER**  **EXTERNAL EXAMINER**

**INSTITUTION VISION AND MISSION**

**Vision**

To emerge as a leader among the top institutions in the field of technical education.

**Mission**

**M1:** Produce smart technocrats with empirical knowledge who can surmount the global challenges.

**M2:** Create a diverse, fully engaged, learner -centric campus environment to provide quality education to the students.

**M3:** Maintain mutually beneficial partnerships with our alumni, industry and professional associations

**DEPARTMENT VISION, MISSION, PEO, PO AND PSO**

**Vision**

To empower the Electronics and Communication Engineering students with emerging technologies, professionalism, innovative research and social responsibility.

**Mission**

**M1:** Attain the academic excellence through innovative teaching learning process, research areas & laboratories and Consultancy projects.

**M2:** Inculcate the students in problem solving and lifelong learning ability.

**M3:** Provide entrepreneurial skills and leadership qualities.

**M4:** Render the technical knowledge and skills of faculty members.

**Program Educational Objectives**

**PEO1:** **Core Competence:** Graduates will have a successful career in academia or industry associated with Electronics and Communication Engineering

**PEO2:** **Professionalism:** Graduates will provide feasible solutions for the challenging problems through comprehensive research and innovation in the allied areas of Electronics and Communication Engineering.

**PEO3:** **Lifelong Learning:** Graduates will contribute to the social needs through lifelong learning, practicing professional ethics and leadership quality

**Program Outcomes**

**PO 1: Engineering knowledge:** Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

**PO 2: Problem analysis:** Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

**PO 3: Design/development of solutions:** Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

**PO 4: Conduct investigations of complex problems:** Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

**PO 5: Modern tool usage:** Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

**PO 6: The engineer and society:** Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

**PO 7: Environment and sustainability:** Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

**PO 8: Ethics:** Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

**PO 9: Individual and team work:** Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

**PO 10: Communication:** Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

**PO 11: Project management and finance:** Demonstrate knowledge and understanding of the engineering and management principles and apply these to one’s own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

**PO 12: Life-long learning:** Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

**Program Specific Outcomes**

**PSO1:** Applying knowledge in various areas, like Electronics, Communications, Signal processing, VLSI, Embedded systems etc., in the design and implementation of Engineering application.

**PSO2:** Able to solve complex problems in Electronics and Communication Engineering with analytical and managerial skills either independently or in team using latest hardware and software tools to fulfil the industrial expectations.

| **Abstract** | **Matching with POs and PSOs** |
| --- | --- |
| RAG, BERT, RAILMADAD, Chatbot, Artificial Intelligence | PO1, PO2, PO3, PO4, PO5, PO6, PO8, PO9, PO10, PO12, PSO1, PSO2 |

|  |  |  |
| --- | --- | --- |
| **S.No.** | **Project Domain** | **Mapping with POs/PSOs** |
| 1. | IoT/Cloud Computing/AI/Machine Learning/Deep Learning | PO1, PO2, PO3, PO4, PO5, PO6, PO8, PO9, PO10, PO11, PO12, PSO1, PSO2 |

**ACKNOWLEDGEMENT**

We gratefully remember our beloved Founder Chairman, (Late) Thiru.M.Kumarasamy, whose vision and legacy laid the formation for our education and inspired us to successfully complete this project.

We extend our sincere thanks to Dr.K.Ramakrishnan, Chairman and Mr.K.R.Charun Kumar, Joint Secretary, for providing excellent infrastructure and continuous support throughout our academic journey.

We are privileged to extend our heartfelt thanks to our respected Principal, Dr.B.S.Murugan, B.Tech., M.Tech., Ph.D., for providing us with a conductive environment and constant encouragement to pursue this project work.

We sincerely thank **Dr.A.Kavitha, M.E., Ph.D.,** **Professor and Head, Department of Electronics and Communication Engineering,** for her continuous support, valuable guidance, and motivation throughout the course of this project.

Our special thanks and deep sense of appreciation go to our **Project Superior, Mr.S.Mohanraj, M.E., (Ph.D).,** Assistant Professor, **Department of Electronics and Communication Engineering**, for his exceptional guidance, continuous supervision, constructive suggestion, and unwavering support, all of which have been instrumental in the successful execution of this project.

We would also like to acknowledge **Dr.S.Vimalnath, M.E., Ph.D., Associate Professor, Class Advisor** and **Project Coordinator**, for his constant encouragement and coordination that contributed to the smooth progress and completion of our project work.

We gratefully thank all the **faculty members of the Department of Electronics and Communication Engineering** for their timely assistance, valuable insights, and constant supporting during various phase of the project.

Finally, we extend our profound gratitude to our **parents and friends** for their encouragement, moral support, and motivation, without which the successful completion of the project would not have been possible.

**ABSTRACT**

The design and implementation of adding Artificial Intelligence to the RAILMADAD program are described in this work. The system is intended to enhance the grievance reporting process for passengers and then investigate their complaints. Additionally, the system equipped with memory-based RAG chatbot to enhance passengers user experience. To reduce the work fatigue for railways employees, to speed up resolving the issue and implementing corrective measures with the office, we implemented a routing algorithm. After analyzing the sentiment surrounding the complaint, this AI model will rank the issue’s urgency for action. To improve the precision and speed of complaint handling, metadata such as location, issues and timestamp are extracted.

To protect the privacy of the passengers, the complaints filed by the passengers are compiled into a tokenized form. For passengers are compiled into a tokenized form. For passengers convenience: 24/7 grievance redressal mechanism, without the human intervention. Privacy: Maintain the privacy of the complaints from the passengers. Efficiency: Increases the speed for the resolution of the given complaints. AI Chatbots: Deploy AI chatbots to provide instant acknowledgment and preliminary response, collecting additional necessary information from the complainant. The Proposed Model: An Bi-directional Encoder representation from Transformers model which analyses user’s complaint input sequences, capturing the underlying character level feature and then classifies them into their respective departments to accurate redressal of complaints. Our model outperforms several highline model achieving an accuracy of 95.93 percent and F1-score of 0.96.

**TABLE OF CONTENTS**

|  |  |  |
| --- | --- | --- |
| **CHAPTER No.** | **CONTENTS** | **PAGE No.** |
|  | **INSTITUTION VISION AND MISSION** | iii |
|  | **DEPARTMENT VISION AND MISSION** | iii |
|  | **DEPARTMENT PEOs, POs AND PSOs** | iv |
|  | **ABSTRACT** | ix |
|  | **LIST OF TABLES** | xii |
|  | **LIST OF FIGURES** | xiii |
|  | **LIST OF ABBREVIATIONS** | xiv |
| **1** | **INTRODUCTION** | **1** |
|  | 1.1 Objective | 4 |
|  | 1.2 RailMadad System Architecture and Workflow | 5 |
|  | 1.3 AI-Enhanced RailMadad System | 6 |
| **2** | **LITERATURE SURVEY** | **10** |
| **3** | **EXISTING SYSTEM`** | **13** |
| **4** | **PROPOSED SYSTEM** | **19** |
|  | 4.1 Emergency Detection | 21 |
|  | 4.2 Bidirectional Training | 22 |
|  | 4.3 Transformers Architecture | 23 |
|  | 4.4 BERT Architecture | 24 |
| **5** | **RESULTS AND DISCUSSION** | **31** |
|  | 5.1 Model Performance and Evaluation | 31 |
|  | 5.2 Model Stability and Learning Behavior | 32 |
|  | 5.3 Confusion Matrix Analysis | 33 |
|  | 5.4 Real-world Implications | 34 |
|  | 5.5 System Optimization and Scalability | 36 |
|  | 5.6 Model Performance and Accuracy | 38 |
|  | 5.7 Model Comparison | 39 |
|  |  |  |
| **6** | **CONCLUSION AND FUTURE WORK** | **49** |
|  | **REFERENCES** | **51** |

**LIST OF TABLES**

|  |  |  |
| --- | --- | --- |
| **TABLE No.** | **TITLE** | **PAGE No.** |
| 5.1 | Confusion Matrix | 33 |
| 5.2 | Evaluation results on our dataset | 33 |
| 5.3 | Model Comparison | 43 |

**LIST OF FIGURES**

|  |  |  |
| --- | --- | --- |
| **FIGURE No.** | **TITLE** | **PAGE No.** |
| 1.1 | RailMadad Architecture workflow | 5 |
| 1.2 | Enhancing RailMadad with AI | 8 |
| 3.1 | Existing Methodology | 17 |
| 4.1 | Proposed Methodology | 22 |
| 4.2 | Block Diagram | 23 |
| 4.3 | BERT Model | 24 |
| 5.1 | Average and Standard deviation loss | 32 |
| 5.2 | Model Comparison | 44 |

**LIST OF ABBREVIATIONS**

|  |  |  |
| --- | --- | --- |
| **ACRONYM** |  | **ABBREVIATION** |
| RAG | - | Retrieval-Augmented Generation |
| AI | - | Artificial Intelligence |
| IR | - | Indian Railways |
| NLP | - | Natural Language Processing |
| BERT | - | Bidirectional Encoder Representations from Transformers |
| SQL | - | Structured Query Language |
| CRN | - | Complaint Registration Number |
| RNN | - | Recurrent Neural Networks |
| DMAF | - | Deep Multimodal Attentive Fusion |
| ASR | - | Automatic Speech Recognition |
| SMS | - | Short Message Services |
| RM | - | RailMadad |
| CLS | - | Color Light Signal |
| PNR | - | Passengers Name Record |
| MLM | - | Masked Language Modelling |
| NSP | - | Next Sentence Prediction |
| API | - | Application Programming Interface |
| Graph SQL | - | Graph-based Structured Query Language |
| MTM | - | Mark to Market |
| LSTM | - | Long Short-Term Memory |
| SMU | - | Suburban Multiple Unit |

**CHAPTER 1**

**INTRODUCTION**

India has recently surpassed China to become the world’s most populous country. Train travel is a popular choice for long journeys in India, thanks to its ease, comfort and affordability. However, various factors such as the quality of food, coach, cleanliness, seat quality, and number of passengers can make train travel less enjoyable. Passenger traffic: In 2022, Indian Railways carried about 8 billion passengers. Indian Railways operates over 13,000 passenger trains daily. Indian Railways is one of the largest railway system in the world, with 7,349 stations and 132,310 kilometers (82,210 miles) of track. IR is owned and operated by the Indian government and comes under the control of the Ministry of Railways. IR operates passenger trains daily and also handles fright and mail operations.

The railway industry servers as a crucial backbone for the Indian transportation system globally, facilitating efficient travel for vast passenger complaints and concerns effectively remains a significant challenge for railways authorities. The RailMadad platform, initiated by Indian Railways, aims to address this issue providing a centralized complaint management system. Despite its efforts, the platform faces challenges in efficiently managing and resolving passenger to give the most positive feedback to the system to passengers efficiency and secure. In a country as vast and populous as India, the Indian Railways serves as the lifeline of transportation.

Every day, millions of passengers use rail services, making it inevitable that complaints and grievances arise. Traditionally, the management of these complaints has relied on manual processes—human staff reading, sorting, and resolving each issue individually. While this approach may have worked in earlier times, it has become increasingly inefficient with the growing volume of travelers. Delays, mismanagement, and unresolved grievances have contributed to passenger dissatisfaction, affecting the overall image and trust in the Indian Railways.

To address these concerns, the integration of cutting-edge technologies like Natural Language Processing (NLP**)** and Retrieval-AugmentedGeneration (RAG)offers a transformative solution. The proposed system envisions an intelligent, automated complaints management framework within the existing RailMadad platform. This innovation aims to streamline the handling of passenger complaints, ensuring timely and accurate responses that ultimately enhance user satisfaction. Natural Language Processing plays a crucial role in this system by enabling the computer to understand, interpret, and process human language.

When a passenger submits a complaint about cleanliness, train delays, or staff behavior—the NLP engine analyzes the text, identifies key themes, and classifies it into predefined categories. This initial analysis includes sentiment detection, urgency evaluation, and keyword extraction, allowing the system to prioritize more severe or sensitive issues. At the core of the resolution mechanism lies the Retrieval-Augmented Generation (RAG) model, a deep learning technique that combines the strengths of information retrieval and generative models.

Unlike traditional chatbots that rely solely on static databases or scripted responses, RAG retrieves relevant documents or past case records and uses a language generation model to craft a coherent, context-aware response. This not only enhances the accuracy of replies but also supports human agents by suggesting solutions drawn from a vast knowledge base of previous complaints and resolutions. Furthermore, the integration of a deep learning-based complaint classification modelallows for the automation of task allocation. Once a complaint is classified, the system intelligently routes it to the appropriate department—such as operations, sanitation, catering, or security—minimizing delays and reducing dependency on manual filtering. The benefits of this system are multifaceted.

Passengers experience faster, more personalized resolutions. Railway staff face reduced workload and clearer task assignments. The administration gains access to real-time dashboards that track trends, response times, and satisfaction levels, leading to more informed decision-making. Looking forward, this system can be expanded to support voice-based complaint registration, regional language processing, and even a chatbot interface for real-time assistance. The vision is to create a seamless, intelligent, and responsive complaints management ecosystem that aligns with the goals of Digital India and the modernization of public infrastructure. In today’s fast evolving digital age, businesses are continuously targeting to deliver excellent customer service.

To meet this demand, many are turning to AI-powered solutions, such as Retrieval Augmented Generation (RAG) model chatbots. These innovative chatbots revolutionize complaint management by offering immediate assistance, personalized support, and efficient resolutions. By leveraging a vast knowledge base of relevant information, RAG models can quickly understand customer issues, provide accurate and consistent responses, and seamlessly escalate complex cases to human agents. This not only improves the customer experience but also optimizes internal operations, reduces costs, and improves overall operational efficiency.

**1.1 OBJECTIVE**

The primary objective of this project is to revolutionize the grievance redressal mechanism within Indian Railways by integrating cutting-edge Artificial Intelligence technologies into the existing RailMadad system. Indian Railways, being one of the largest railway networks in the world, caters to an enormous population daily. With such a massive scale of operations, passenger complaints and grievances are inevitable. This project seeks to bridge the existing gaps by embedding AI-driven modules that can interpret, classify, prioritize, and route passenger complaints intelligently and automatically.

By utilizing Natural Language Processing (NLP) and the Bidirectional Encoder Representations from Transformers (BERT) model, the system is designed to understand the sentiment and context behind a complaint, identifying emergency situations and ensuring faster response times. Furthermore, incorporating a Retrieval-Augmented Generation (RAG) based chatbot provides 24/7 assistance to passengers, enabling them to interact with the system in a human-like manner, receive instant responses, and obtain status updates. Another major objective is to extend the accessibility of the system through voice input support, recognizing that not all users may be comfortable with or capable of typing their complaints. This is achieved using robust speech recognition tools like Whisper, allowing passengers to lodge their grievances via voice calls in multiple Indian languages. Moreover, the use of Graph SQL ensures that complaints are dynamically routed to the appropriate departments based on metadata such as location, urgency, and complaint type, thereby reducing manual overhead and improving accuracy. The broader vision of this project is to enhance the overall passenger experience by building a faster, smarter, and more inclusive complaint management ecosystem.

**1.2 RAILMADAD SYSTEM ARCHITECTURE AND WORKFLOW**

The figure 1.1 titled “Objective of the Project” presents a structured overview of the primary and secondary goals that drive the enhancement of the RailMadad grievance redressal system using Artificial Intelligence. At the center of the diagram lies the core objective to enhance RailMadad with AI for smart grievance redressal. This central aim is surrounded by several key sub-objectives, each representing a crucial component that collectively contributes to achieving the project’s overall vision. The RailMadad Systemis a modern, AI-driven grievance redressal platform developed to efficiently handle passenger complaints in the Indian Railways ecosystem. The system follows a structured pipeline of data acquisition, intelligent analysis, classification, and action routing - all enhanced through state-of-the-art Artificial Intelligence and machine learning models.

Passenger

Prioritization

Passenger

Routing



Voice Input Support

RAG-Based

Chatbot

Enhanced Passenger Experience

**Figure 1.1 RailMadad Architecture Workflow**

Complaints can be registered through various input modes such as:

1. Mobile Applications
2. Web Portals
3. Social Media (Twitter, Facebook, etc..)
4. Helpline Number
5. Voice Calls

**Voice-to-Text Module:** For voice-based complaints, especially from helpline calls or app voice input. Example, Whisper AI (an Automatic Speech Recognition System) converts audio inputs into text. The converted text is then normalized and prepared for further analysis.

**1.3 AI-ENHANCED RAILMADAD SYSTEM**

The Indian Railways, being one of the largest transportation networks in the world, faces an enormous challenge in addressing the grievances of millions of passengers each day. With the evolution of technology and the increasing demand for timely and transparent customer service, the integration of Artificial Intelligence (AI) into the RailMadad grievance redressal platform marks a transformative shift in public service delivery. The AI-enhanced RailMadad system introduces numerous advantages that redefine how complaints are processed, prioritized, and resolved.

1. Faster Complaint Resolution
2. Improved Accuracy in classification
3. 24/7 Accessibility and Responsiveness
4. Multilingual and Inclusive Design
5. Reduced Human Dependency
6. Real -Time Monitoring and Analytics

**How the AI-Based Madad System Works:** The AI-integrated RailMadad system operates through a structured, intelligent workflow that automates and enhances the traditional grievance redressal process. Designed to improve complaint resolution speed, accuracy, and accessibility, the system employs modern technologies such as Natural Language Processing (NLP), machine learning, voice recognition, and chatbot interaction to handle thousands of daily complaints with efficiency and precision. Here's a step-by-step overview of how the system works. The RailMadad system, enhanced with Artificial Intelligence (AI), represents a significant leap in the way grievances are addressed within Indian Railways. This intelligent system is designed to streamline the complaint registration process, improve classification accuracy, prioritize emergencies, and enhance the overall passenger experience through automation and real-time communication.

The system operates through a series of well-defined and interconnected stages that ensure complaints are handled quickly, efficiently, and with minimal manual intervention. The journey begins when a passenger experiences an issue during their travel. To register a complaint, the passenger can choose from a variety of convenient platforms — including the RailMadad mobile application, official website, helpline number (139), or even social media platforms such as Twitter and Facebook. This multichannel support ensures that the system remains accessible to users from different demographics, including those in rural areas or without smartphones.

For voice-based complaints, particularly those made via phone calls, the system employs a powerful speech-to-text model known as Whisper, developed by OpenAI. This tool transcribes the spoken complaint into text with high accuracy, even in different Indian languages. This transcription step is critical as it allows the voice input to be seamlessly integrated into the system’s digital processing pipeline. Once the complaint is available in text form, it is processed by a Natural Language Processing (NLP) model, specifically the Bidirectional Encoder Representations from Transformers (BERT)**.**

Multichannel Input Compatibility

Emergency Detection

Emergency Detection

Characteristics of the RailMadad AL-Based Grievance Redressal System

Dashboard for Monitoring and Analytics

Retrieval-Augmented

Chatbot (RAG)

Real-Time Tracking and Notifications

Multilingual and voice support

Real-Time Tracking and Notifications

**Figure 1.2 Enhancing RailMadad with AI**

BERT analyzes the text to extract meaning, tone, and urgency. This deep language understanding allows the system to accurately interpret user intent, classify the complaint category (such as ticketing, sanitation, or catering), and determine whether the issue is routine or an emergency. If the system detects that the complaint is of a critical nature, such as a medical emergency, safety threat, or technical malfunction - it flags the complaint for immediate action. This is made possible through a combination of keyword analysis, sentiment detection, and contextual inference.

Emergency complaints are assigned the highest priority in the routing system, ensuring they are escalated to the appropriate railway authorities without delay. Throughout this entire process, the passenger remains informed via an AI-powered Retrieval-Augmented Generation (RAG) chatbot**.** This chatbot confirms that the complaint has been received, provides a Complaint Registration Number (CRN), and offers real-time updates on the complaint’s progress. It also answers general queries and directs users to relevant information, mimicking a human support agent - but with the speed and consistency of AI. From the administrative side, railway officials have access to a centralized dashboard where they can monitor incoming complaints, view statistics, and track the performance of their respective departments. This dashboard enables them to identify patterns in passenger grievances, detect recurring issues, and make informed decisions to improve service quality.

**Benefits of the AI-Enhanced RailMadad System:**

1. AI-enhanced system is the dramatic reduction in complaint resolution time**.**
2. Another key benefit lies in the accuracy of complaint categorization**.**
3. The inclusivity and accessibility of the platform have also seen remarkable improvements.
4. The real-time communication and transparencyprovided by the RAG-based chatbot.
5. The AI-enhanced RailMadad system offers actionable insights and data-driven decision-making tools**.**

**CHAPTER 2**

**LITERATURE SURVEY**

In the rapidly evolving landscape of public service and digital governance, Artificial Intelligence has emerged as a powerful tool to revolutionize how institutions interact with citizens. This literature survey explores existing research and technological advancements that inform the development of an AI-integrated complaint redressal system, specifically tailored to Indian Railways’ RailMadad platform. The foundation of this study is rooted in the challenges faced by traditional grievance systems in public transportation. According to Prashant Kumar Dubey et al. [1]**,** the existing mechanisms of complaint registration in Indian Railways were fragmented and lacked uniformity. The authors highlighted the inefficiencies of handling passenger complaints via disconnected channels such as registers, helplines, and social media. They proposed a centralized system like RailMadad to streamline the process. While the study effectively emphasized the need for unification, it also pointed to the shortcomings in speed, accountability, and user satisfaction—areas where Artificial Intelligence could provide a transformative edge.

A significant breakthrough in Natural Language Processing (NLP), and a cornerstone of this project, was introduced by Ashish Vaswani et al. [2] through the paper “Attention Is All You Need”. This seminal work introduced the Transformer model, which shifted the paradigm from traditional Recurrent Neural Networks (RNNs) to attention-based models. The self-attention mechanism allowed models to consider the entire context of a sentence, both forward and backward, enabling deeper understanding. This innovation led to the development of BERT a pre-trained language model that has been extensively used in the AI-enhanced RailMadad system to understand and classify complaints with high accuracy. Understanding not just what passengers say, but how they say it, is essential to improving service delivery.

In this context, Stuart J. Miller et al. [5] explored the fusion of metadata with textual input to improve classification systems. Their work illustrated that by incorporating information such as complaint timestamps, location, and tags, models could make more context-aware decisions. This concept strongly influenced the routing mechanism of the proposed system, where metadata plays a key role in forwarding complaints to the appropriate department. The detection of urgency and emotional tone in a complaint is another essential feature of a smart redressal system.

Feiran Huang et al. [6] introduced Deep Multimodal Attentive Fusion (DMAF), which highlighted how attention mechanisms could be used to perform sentiment analysis across different data modalities. Although our project focuses primarily on text and voice, the emphasis on sentiment plays a major role in determining whether a complaint is categorized as an emergency. Using BERT, the system can distinguish between routine feedback and critical issues requiring immediate intervention. Accessibility is a core concern when designing inclusive public systems. Many passengers in India may prefer or need to lodge complaints through voice rather than text. In this regard, Vinnarasu A et al. [7] proposed an approach to improve speech recognition systems by incorporating natural language punctuation and sentence structure into speech-to-text outputs. Building on this idea, our system uses Whisper**,** an advanced, multilingual Automatic Speech Recognition (ASR) system developed by OpenAI, to convert voice complaints into text with high accuracy. This makes the complaint process more inclusive, especially for users who are not literate or tech-savvy.

Patrick Lewis et al. [9]introduced the concept ofRetrieval-Augmented Generation (RAG)**,** which blends information retrieval and text generation to create highly relevant responses. In our system, the RAG-based chatbot provides passengers with instant responses, complaint status updates, and assistance with frequently asked questions. This not only enhances the user’s experience but also ensures consistent and reliable communication. Finally, the challenge of routing complaints accurately and efficiently is tackled through the use of graph-based databases. Modern literature, such as Yuanyuan Tian [10]andMaciej Besta et al. [11]**,** has emphasized the power of Graph SQL in modeling complex relationships. In our system, complaints are routed dynamically by mapping complaint types, departments, and geographic divisions as interconnected nodes. This ensures the complaint reaches the most appropriate authority in minimal time, greatly enhancing operational efficiency. In summary, the literature strongly supports the use of AI technologies—such as NLP.

**CHAPTER 3**

**EXISTING SYSTEM**

Before the integration of Artificial Intelligence, the grievance redressal mechanism within Indian Railways operated largely through manual or semi-automated processes, which, although functional, were not optimized for the scale and diversity of India's passenger base. The existing RailMadad system, introduced as a centralized complaint management platform, aimed to unify various channels of complaint intake. While this system was a major step forward in bringing accessibility and transparency to railway services, it still faced several operational challenges that limited its effectiveness. Under the existing setup, passengers could lodge complaints through a variety of channels: the RailMadad mobile application, the official web portal, social media platforms, emails, SMS, direct phone calls to helpline number 139, and manual complaint registers at railway stations.

Each of these methods functioned as an entry point for grievances, but the data from these sources was not always integrated or analyzed cohesively. Although RailMadad provided a central dashboard to view and monitor complaints, it lacked the intelligence to interpret and prioritize them based on urgency or context. One of the primary drawbacks of the current system is the manual categorization of complaints**.** Once a complaint is lodged, it is forwarded to the department concerned manually by operators, who must interpret the nature of the complaint, determine its relevance, and assign it to the appropriate authority. This process is time-consuming and highly susceptible to human error.

Additionally, this approach does not scale well during periods. Moreover, the system does not support automatic prioritization of emergency complaints**.** There is no mechanism in place to detect if a complaint is a medical emergency, a safety threat, or a service disruption that needs immediate intervention. As a result, critical issues may be delayed or overlooked in the queue of general complaints, potentially risking passenger safety and damaging the reputation of Indian Railways. Another notable limitation is the lack of intelligent feedback and learning**.**

The current system does not adapt or improve based on historical complaint data or passenger behavior. There is no facility to learn from previous resolutions or to recommend best practices to departments based on recurring issues. One of the most significant limitations of the existing system lies in its manual complaint categorization and routing. After a complaint is submitted, it is manually reviewed by back-end staff who must assess its relevance and forward it to the appropriate department. This human-dependent process isslow, prone to error, and does not scale well during peak times—such as during major holidays, festival seasons, or large-scale train delays—when complaint volumes surge dramatically.

Additionally, the current system lacks the capability to identify and prioritize emergency or high-urgency complaints. There is no built-in mechanism for determining whether a complaint pertains to critical issues such as health emergencies, passenger safety, on-board equipment failure, or security threats. Consequently, all complaints are treated equally, and urgent matters may remain unaddressed in the queue of regular issues, thereby compromising passenger safety and diminishing public confidence in the railway system. Another critical gap is the absence of intelligent feedback loops and learning mechanisms. The system does not analyze historical complaint data to identify trends, recurring issues, or performance bottlenecks within departments. It lacks the capability to suggest best practices or route common complaints proactively based on previously resolved cases. This deficiency leads to redundant work, delays in resolution, and missed opportunities to improve services systematically. Another limitation of the existing platform is the language and accessibility barrier.

While the system supports basic complaint entry in English and Hindi, it does not offer seamless multilingual input for India’s diverse linguistic population. There is also no provision for voice-based complaint registration, which could be crucial for elderly passengers, visually impaired users, or those with limited literacy. From the administrative perspective, the system does include a performance monitoring dashboard, but its functionality is limited. It offers only basic metrics such as the number of complaints received, closed, or pending. It lacks advanced analytical features such as real-time performance monitoring, sentiment mapping, predictive analytics, or trend forecasting.

As a result, senior officials and department heads do not have the necessary insights to take proactive action or make informed policy decisions based on live data. This absence of a learning mechanism results in repetitive delays and missed opportunities to optimize processes. The user interaction experience in the existing system is also limited. Passengers typically receive a confirmation message and a Complaint Registration Number (CRN) after lodging a complaint, but updates are not always timely or informative. Many users are left in the dark about the status of their complaint, leading to frustration and mistrust. Moreover, passengers must wait for human responses during working hours, as there is no automated chatbot or 24/7 support system integrated into the platform. While the RailMadad system does provide a basic performance dashboard for railway officials, the insights it offers are minimal. It lacks real-time analytics**,** trend identification, and predictive capabilities, which are essential for a data-driven organization operating at the scale of Indian Railways.

Departmental performance is measured primarily through response times and complaint closure rates, without deeper insights into complaint. In summary, the existing RailMadad system, despite being a unified portal for grievance redressal, suffers from several shortcomings:

1. Heavy dependence on manual processing
2. Inability to prioritize emergency issues
3. Lack of real-time, automated communication
4. Limited feedback utilization and learning
5. Inadequate user engagement and transparency

These limitations highlight the urgent need for an AI-driven upgrade that can automate, analyze, and intelligently manage the lifecycle of each complaint. The proposed system seeks to bridge these gaps by integrating advanced AI tools, thereby transforming RailMadad into a smart, scalable, and responsive grievance redressal platform. In essence, the proposed system builds a smart, scalable, and citizen-centric platform that reimagines how Indian Railways manages passenger grievances. It reduces the burden on human operators, minimizes response time, and empowers passengers through transparency and accessibility. By combining cutting-edge AI technologies with an intuitive user experience, this system sets a new benchmark in public grievance management.

Earlier, there was no single system for handling complaints. Passengers could complaint through different channels like letters, social media, SMS, email, the website, and the app. In addition, Railways also had seven different helplines for various kinds of complaints. Before, there was no single place where all complaints were collected. This made it hard to track and solve problems because complaints could be filed in many different ways, and there was no way to know if the same complaint was being reported multiple times. The third-party dashboard is used to file complaints, and the agent can handle them by using the passengers' mobile phones. Complaints are transferred from the third-party dashboard to the RailMadad dashboard.

Twitter& Facebook

Post/DM by Agent

Third-party Dashboard

RailMadad Dashboard

Complaint Registered & CRN generated through RM System

M

Final Resolution on RailMadad (Notification on agent)

Agent to take Mobile number from complaint through DM

M

Agent to lodge complaint on RailMadad

M

CRN sent to complaint through RM System

M

Agent to lodge complaint on RailMadad

NLP

**Figure 3.1 Existing Methodology**

The agent will file the complaint on RailMadad, which will then create complaints register and a Complaint Register Number (CRN). After the third party receives the final resolution, they notify the passengers. Another key feature of the proposed system is its **feedback loop,** which is triggered once a complaint is marked as resolved. Users are prompted to share their satisfaction level and additional comments. This feedback is then used to further train the AI models, improve response strategies, and enhance the accuracy of classification and routing over time.

**CHAPTER 4**

**PROPOSED SYSTEM**

The proposed method for enhancing the RailMadad grievance redressal platform leverages the transformative capabilities of Artificial Intelligence (AI) to create a smart, scalable, and automated complaint management system. While the current system provides a centralized space for registering complaints, it lacks the intelligence to process, prioritize, and respond to them efficiently. The proposed method introduces a multi-layered architecture that integrates Natural Language Processing (NLP), voice recognition, sentiment analysis, chatbot communication, and intelligent routing, all working cohesively to deliver a seamless and responsive experience for both passengers and railway staff. The foundation of the proposed method begins with multi-source complaint acquisition. Passengers can register complaints through various input modes such as the RailMadad mobile app, official website, helpline (139), and social media platforms. Additionally, voice-based input is introduced to cater to passengers who may not be comfortable with typing or are differently abled.

This step ensures inclusivity and accessibility for users from diverse linguistic, regional, and educational backgrounds. To process voice complaints, the system integrates **Whisper,** a state-of-the-art speech recognition model capable of transcribing voice input in multiple Indian languages into accurate text. This transcription is essential for converting audio data into a format compatible with downstream text-processing systems. Once in text format, the complaint is passed through **BERT (Bidirectional Encoder Representations from Transformers)** an advanced NLP model pre-trained on large text corpora. BERT analyzes the structure, context, and sentiment of the complaint. It understands whether the complaint is related to cleanliness, ticketing, catering, safety, or any other department, and classifies it accordingly.

Importantly, BERT is also capable of **emergency detection,** identifying whether a complaint reflects urgency — such as medical emergencies or safety threats — which require immediate escalation. Following classification and urgency tagging, the complaint is forwarded to the **Routing Module,** powered by **Graph SQL**. Unlike traditional relational databases, Graph SQL allows for a more dynamic and interconnected representation of departments, stations, personnel, and complaint types. For example, if a complaint pertains to a broken seat on Train 12623, the routing system identifies not only the train but the specific zone and department in charge of its maintenance.

This intelligent routing system reduces manual effort and minimizes the chances of misrouted or delayed complaints. To provide passengers with **real-time communication,** a **Retrieval-Augmented Generation (RAG)** based chatbot is deployed. This chatbot acts as a virtual assistant, confirming complaint submission, issuing a Complaint Registration Number (CRN), updating users on complaint status, and answering frequently asked questions. Unlike rule-based bots, RAG combines a document retriever with a language generator to provide accurate, context-aware responses drawn from official railway guidelines, policies, and past resolutions.

Railway officials are supported with a **data-driven dashboard** that displays live statistics on complaint trends, department performance, resolution times, and passenger satisfaction scores. This empowers administrators to make informed decisions, deploy resources more. In summary, the proposed method transforms the existing RailMadad system into a highly intelligent and automated framework with the following core components:

* **Voice-to-text complaint registration using Whisper.**
* **NLP-based complaint classification and sentiment analysis using BERT.**
* **Emergency detection and auto-prioritization.**
* **Graph-based complaint routing to relevant departments.**
* **24/7 chatbot interaction via RAG architecture.**
* **Real-time analytics dashboard for officials.**
* **Continuous learning through user feedback.**

This method ensures that passenger grievances are addressed not only faster but more accurately and empathetically, thus redefining how public service complaint systems function in the digital era. This feedback is used not only for accountability but also to refine AI models through continuous learning thereby making the system smarter and more effective over time. Passengers use the RailMadad dashboard to file complaints, which are sent through the system. The Artificial Intelligence is the source of the complaint. The RM system generates the Complaint Registration Number (CRN). The CRN number allows passengers to follow the complaints. The RailMadad program allows users to view real-time updates. The complaint's final resolution was delivered via the RM system.

**4.1 EMERGENCY DETECTION**

Emergency detection is automatically driven text analysis by extracting the keywords from the unstructured complaints. This process involves meticously defining a list of keywords or phrases that signal potential emergencies such as “Medical Emergency”, “Safety and Security for passengers,” based on domain emergency is flagged. While keywords are providing a valuable starting point, understanding the context of the complaint is crucial. Natural language Processing (NLP) techniques can analyze the sentiment, overall meaning and urgency of the complaint. BERT stands for Bidirectional Encoder Representations from Transformers. It is a groundbreaking Natural Language Processing (NLP) model that revolutionized how machines understand and generate human language.

Twitter & Facebook

RailMadad Dashboard

Complaint Registered & CRN generated through RM System

Final Resolution on RailMadad

Complaint lodge through AI

CRN sent to complaint through RM System

Final Resolution sent to complaint through RM System

Post/DM by System

NLP

**Figure 4.1 Proposed Methodology**

**4.2 BIDIRECTIONAL TRAINING**

Traditional model: Earlier models processed text sequentially, either from left to right or right to left. This limited their ability to grasp the full context of a word, as they couldn’t consider both preceding and succeeding words simultaneously. BERT’s Innovation: BERT addresses this limitation by employing bidirectional training. It processes the entire sequences of words in a sentence at once, allowing it to capture intricate relationships between words, regardless of their position within the sentence.

Authority 1

Authority 2

Authority 3

Graph SQL

Passenger feedback

Text form complaints

Chat bot

Voice complaint

BERT

CRN Generation

OpenAI  
Whisper

Sentiment analysis urgency detection

**Figure 4.2 Block Diagram**

**4.3 TRANSFORMERS ARCHITECTURE**

Self-Attention Mechanism: At the heart of BERT lies the Transformer Architecture. This architecture utilizes a powerful mechanism called Self-Attention. Self-attention allows the model to evaluate the significance of different words in a sentence to determine the representation of specific word. This means that the model can focus on the most relevant parts of the sentence, leading to a deeper understanding of the context. BERT’s Innovation: BERT addresses this limitation by employing bidirectional training. It processes the entire sequences of words in a sentence at once, allowing it to capture intricate relationships between words, regardless of their position within the sentence. Railway officials are supported with a **data-driven dashboard** that displays live statistics on complaint trends, department performance, resolution times, and passenger satisfaction scores. This empowers administrators to make informed decisions, deploy resources more effectively, and proactively address recurring issues.

**4.4 BERT ARCHITECTURE**

Probabilities

Dense Layer

+Activation

Token station

TN

Tok N

CLS

Tok 1

T1

C

BERT-BASE

**Figure 4.3 BERT Model**

Encoder-Only Architecture: BERT employs only the encoder part of the Transformer architecture. The encoder is responsible for reading and understanding the input text. Since BERT’s primary goal is to generate language representation, it doesn’t require a decoder for tasks like language translation or text generation. BERT is pre-trained on a colossal amount of unable text data using a self-supervised learning approach. This means that the model learns to represent language patterns and relationships without explicit human annotations. Self-supervised Learning: The pre-trained BERT model can be fine-tuned for the wide range of text classifications tasks such as: Sentiment Analysis: classifying text positive, negative or neutral. Topic classification: categorizing text into predefined topics (e.g., news, sports, politics). Intent classification: Determining the user’s intent from the given text (e.g., “check PNR,” “order tea”).

BERT consistently achieves state-of-the -art results on many text classifications benchmarks, surpassing previous model in accuracy and performance. More than half of the complaints are shared with 139 helplines. This indicates that passengers feel more at ease voicing their complaints over the phone or by voiceover. Thus, we activated RailMadad's voice complaint register. Passengers' use of the system will be improved by turning on voice chat. It improvises the usage of the system of RailMadad more effectively. The model imposes the voice to text converter and validate through the emergency detection module and then continues its verification process. Through the use of a pre-trained model and robust speech recognition via large-scale weak supervision, we are able to condense the passenger’s complaints into text format. Following that, the process was carried out using BERT for sentiment analysis and emergency detection. This is the issue with confirming that the content is a legitimate question or grievance Verification.

The proposed AI-powered RailMadad system leverages cutting-edge language models and speech recognition technology to automate and enhance the way passenger complaints are processed, especially voice-based complaints, which are becoming increasingly popular due to their simplicity and accessibility. At the heart of the system lies BERT (Bidirectional Encoder Representations from Transformers), a state-of-the-art language model developed by Google. BERT employs only the encoder component of the Transformer architecture. The encoder is responsible for reading and deeply understanding the context of the input text. Unlike sequence-to-sequence models (which use both encoder and decoder for tasks like translation), BERT is designed to generate powerful contextual representations of language, making it highly suitable for classification tasks.

BERT’s design allows it to look at text bidirectionally, i.e., it reads the entire sentence at once rather than from left to right or right to left. This feature enables it to capture the meaning of words in context, an essential capability when interpreting diverse, unstructured passenger complaints. BERT is pre-trained on massive corpora of unlabeled text using self-supervised learning. This means the model learns patterns, relationships, and meanings within the text without the need for human-annotated data. During pre-training, tasks like Masked Language Modeling (MLM) and Next Sentence Prediction (NSP) help the model understand syntax and semantics.

Once pre-trained, BERT can be **fine-tuned** for a variety of downstream NLP tasks, including:

* **Sentiment Analysis**: Identifying whether a passenger’s complaint expresses a positive, negative, or neutral tone.
* **Topic Classification**: Categorizing the complaint into predefined topics (e.g., sanitation, catering, ticketing).
* **Intent Detection**: Understanding the user's objective from the text (e.g., “file complaint,” “check status,” “request refund”).

BERT has consistently outperformed traditional models across these tasks, setting new benchmarks in text classification accuracy. The voice complaint module is powered by Whisper, an advanced Automatic Speech Recognition (ASR) model developed by OpenAI. Whisper uses large-scale weak supervision to accurately transcribe spoken language into written text, even in noisy environments and multiple Indian languages. Once transcribed, the text is passed through the BERT-based emergency detection and classification pipeline. The workflow is as follows.

1. **Voice Input**: Passenger records their complaint via app, helpline, or mic interface.
2. **Speech Recognition**: Whisper converts audio into clean, structured text.
3. **Complaint Verification**: The text is analyzed to determine if it constitutes a valid complaint, query, or irrelevant content.
4. **Sentiment and Intent Analysis**: BERT examines emotional tone and identifies the purpose of the complaint.
5. **Emergency Detection**: If urgent keywords or negative sentiment are detected, the system flags the complaint for high-priority handling.
6. **Routing**: Verified complaints are routed to the appropriate department via the Graph SQL system.

This layered approach ensures that **only genuine complaints are processed**, while also enabling real-time classification and prioritization**.**

**Impact of voice enabled complaints:** The introduction of voice chat functionality significantly enhances the usability of the RailMadad system. It democratizes access to the grievance redressal process, especially for elderly passengers, those with disabilities, or individuals in low-literacy regions. By integrating voice-to-text, sentiment analysis, and emergency detection, the system ensures that every complaint is understood in context—just as a human officer would, but with greater speed and consistency. In an effort to modernize and enhance the efficiency of the Indian Railways' grievance redressal system, the proposed method introduces a comprehensive, AI-powered framework to automate complaint processing under the RailMadad platform.

The system has been carefully designed to overcome the inefficiencies of manual complaint handling by leveraging technologies such as Natural Language Processing (NLP), speech recognition, intelligent routing, and real-time conversational agents. This integration not only improves operational efficiency but also enhances passenger experience through accessibility, transparency, and responsiveness. At the heart of the proposed method is the understanding that complaints may originate through various sources and formats. In a country as linguistically and technologically diverse as India, it is essential to provide passengers with multiple ways to register their grievances. The system, therefore, supports complaint intake from multiple channels including the RailMadad mobile application, official web portal, helpline number (139), and even popular social media platforms.

Notably, the integration of voice-based input through phone calls or in-app speech interfaces has been prioritized, as data suggests that a significant number of passengers prefer to communicate grievances orally rather than in written form. To accommodate this preference, the proposed method incorporates **Whisper**, a sophisticated speech-to-text engine developed by Open AI. Whisper is capable of recognizing multiple Indian languages and regional accents, and it accurately transcribes voice inputs into structured text, even in noisy environments. This transcription process ensures that spoken complaints are seamlessly brought into the digital ecosystem, making the system inclusive and user-friendly. Once the complaint is converted to text, it undergoes a series of preprocessing steps. This includes cleaning the data, removing irrelevant characters or noise, and normalizing it for language and structure. The cleaned text is then analyzed by **BERT (Bidirectional Encoder Representations from Transformers)**, a state-of-the-art NLP model that understands context and language at a deep level.

BERT plays a critical role in the system by performing sentiment analysis, classifying the complaint by category (such as sanitation, catering, ticketing, etc.), and identifying whether the content signifies an emergency situation. The **emergency detection** capability is particularly significant. Traditional systems often treat all complaints with equal priority, which can result in delayed responses to critical issues. In contrast, the AI-based model is trained to recognize urgency through emotional tone, specific keywords, and contextual cues, enabling the system to escalate urgent cases—such as safety threats or medical needs—for immediate attention.

To keep passengers informed and engaged, a Retrieval-Augmented Generation (RAG) based chatbot is embedded into the platform. This chatbot operates round-the-clock and serves as a virtual assistant that confirms complaint registration, provides real-time status updates, and answers common questions. By combining document retrieval with generative responses, the chatbot can deliver human-like, contextually relevant answers in a conversational format. Moreover, its multilingual capabilities ensure accessibility for a broader range of users. The system also features an **interactive dashboard** for railway officials. This dashboard provides real-time analytics and visualizations, allowing decision-makers to monitor complaint trends, departmental performance, and resolution rates. It acts as a powerful tool for governance and accountability, equipping officials with the insights needed to make timely, data-driven decisions.

Finally, the system closes the loop with a **feedback and learning mechanism**. After a complaint has been resolved, passengers are invited to submit feedback on the quality of the response. This information is logged and analyzed to identify areas for improvement. In addition, feedback data is used to retrain and fine-tune the AI models, making the system increasingly intelligent and adaptive over time.

**CHAPTER 5**

**RESULTS AND DISCUSSION**

The implementation of an AI-powered complaint management system for the RailMadad platform marks a significant advancement in streamlining and automating passenger grievance resolution in the Indian railway ecosystem. The results obtained from the experiments validate the effectiveness and accuracy of the proposed methodology, especially the integration of BERT and other supporting AI models such as the RAG-based chatbot.

**5.1 MODEL PERFORMANCE AND EVALUATION**

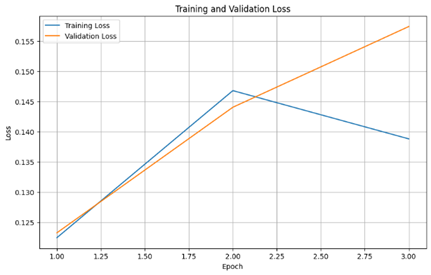
To evaluate the system, a binary classification model was trained to categorize complaints into **emergency** and **non-emergency** types. The dataset, comprising over 4000 complaints sourced from platforms like Twitter, Instagram, and Reddit, was filtered to 2694 data points due to computational constraints. Of these, 263 instances were used for testing and the remaining for training and validation. Key evaluation metrics including **Accuracy, Precision, Recall**, and **F1-score** were used to assess model performance. The system achieved outstanding results:

1. **Accuracy**: 95.93%
2. **Precision**: 95.94%
3. **Recall**: 95.93%
4. **F1-score**: 96.61%

These results demonstrate the model’s robustness in correctly identifying the urgency level of complaints. The high F1-score, in particular, indicates a well-balanced trade-off between precision and recall, crucial for minimizing false alarms while ensuring genuine emergencies are addressed promptly.

**5.2 MODEL STABILITY AND LEARNING BEHAVIOR**

The graph depicts the average and standard deviation of loss over different epochs. The consistently lower standard deviation in training loss compared to validation loss suggests good generalization and model stability. Moreover, the gradual decline in loss without signs of overfitting emphasizes the model’s capacity to learn effectively from limited training data while still performing reliably on unseen data. Additionally, the comparison with other baseline models, as shown in Figure 5.1, reveals that the BERT model outperforms traditional machine learning and older deep learning models, reinforcing its suitability for nuanced tasks like sentiment analysis and emergency detection in complaint text. After training, the BERT model compares with the other model’s average loss throughout each epoch. The picture also shows that, without becoming over-fitted, the model's error rate drops as the number of training epochs rises.



**Figure 5.1 Average and standard deviation of loss**

**5.3 CONFUSION MATRIX ANALYSIS**

The confusion matrix further elucidates the model’s performance, illustrating a balanced prediction pattern with minimal misclassifications. This clarity in classification is particularly critical for emergency routing, where even a single false negative can result in delayed response to a high-priority issue. The matrix shows a strong correlation between predicted and actual outcomes, with a near-perfect balance of true positives and true.

|  |  |  |
| --- | --- | --- |
| Training Set | | |
| TARGET  OUTPUT | Class0 | Class1 |
| Class0 | 430  48.53% | 8  0.90% |
| Class1 | 26  2.93% | 422  47.63% |

**Table 5.1 Confusion Matrix**

**Table 5.2 Evaluation results on our dataset**

|  |  |
| --- | --- |
| Parameter | Result |
| Accuracy | 0.959368 |
| Recall | 0.959368 |
| Precision | 0.959458 |
| F1 Score | 0.966134 |

These metrics are crucial for assessing the performance of classification model, particularly in scenarios where the dataset might be imbalanced (i.e., one has significantly more instances than others). By thoroughly analyzing these metrics, you can better understand your models’ strengths and weaknesses.

**5.4 REAL-WORLD IMPLICATIONS**

The application of this model has profound practical benefits for the Indian Railways. By automating complaint categorization and routing using AI, the average response time is significantly reduced. Previously, 85% of complaints were resolved within two hours. The current system builds on this by automating urgency detection, improving accuracy, and eliminating human bottlenecks. It offers scalable efficiency without compromising quality or safety. The integration of a **voice-to-text module** also accommodates passengers who prefer verbal complaints, which form a significant share of user input. Through speech recognition (using Whisper), voice complaints are transcribed and routed just like text-based complaints, ensuring inclusivity and seamless processing.

Moreover, the **RAG-based chatbot** enhances user experience by providing immediate acknowledgment and preliminary support, increasing trust in the system. Its self-learning ability ensures that with continued use, it becomes more accurate and context-aware. The deployment of the proposed AI-based model holds substantial practical significance for the Indian Railways, particularly in enhancing the efficiency and responsiveness of the **RailMadad** grievance redressal system. Traditionally, complaint management relied heavily on manual processing, which was time-consuming and prone to delays, often leading to passenger dissatisfaction. Although the existing system already achieved an impressive resolution rate with 85% of grievances addressed within two hours, there remained notable challenges related to prioritization and real-time response, especially in high-volume scenarios.

The newly integrated AI system significantly improves upon this by **automating both complaint categorization and urgency detection**, effectively reducing the dependency on human intervention. By leveraging advanced Natural Language Processing (NLP) techniques, the system is capable of analyzing the sentiment and semantics of passenger complaints to determine the level of urgency. This automation streamlines the routing process, ensuring that critical complaints, such as those involving safety or medical emergencies, are prioritized and directed to the appropriate authorities without delay. Consequently, this not only reduces the average response time but also enhances the accuracy of task delegation, ultimately boosting the overall operational efficiency.

Furthermore, one of the standout features of the proposed system is the **voice-to-text complaint processing module**, which addresses the needs of passengers who prefer verbal communication. It is observed that a significant number of users lodge complaints via helpline calls, making voice input an essential component of the system. Utilizing **OpenAI’s Whisper speech recognition model**, the system accurately transcribes spoken grievances into text. These transcriptions are then subjected to the same AI-driven categorization and routing process as textual complaints. This approach ensures inclusivity, catering to passengers who may not be comfortable with digital interfaces or who lack access to smartphones or the internet. The inclusion of a **Retrieval-Augmented Generation (RAG)-based chatbot** further augments the user experience by offering instant responses and acknowledgments.

Passengers receive immediate feedback upon lodging a complaint, which enhances trust and transparency. The chatbot can also provide preliminary solutions, collect additional relevant data, and escalate unresolved or complex issues to human operators. Notably, the chatbot is designed with **self-learning capabilities**, enabling it to improve over time by learning from past interactions, updating its knowledge base, and adapting to evolving complaint patterns. This continuous learning loop makes the system more intelligent and reliable with sustained use.

Overall, this AI-enhanced RailMadad system represents a **scalable and sustainable solution** that addresses both the qualitative and quantitative aspects of complaint management. It maintains high levels of service quality while accommodating the massive scale of operations within Indian Railways. By effectively merging automation, speech recognition, natural language understanding, and machine learning, the system sets a new benchmark for public service complaint management in large-scale transportation networks. Moreover, the **RAG-based chatbot** enhances user experience by providing immediate acknowledgment and preliminary support, increasing trust in the system. Its self-learning ability ensures that with continued use, it becomes more accurate and context aware.

**5.5 SYSTEM OPTIMIZATION AND SCALABILITY**

The backend infrastructure, using **Fast API** and **Flask**, provides high responsiveness and modularity, enabling real-time complaint tracking and CRN generation. The use of **Graph SQL** further improves data retrieval and routing efficiency by leveraging relationship-based data modeling. This design allows the system to scale across the Indian Railways’ vast network of over 13,000 trains and 7,000 stations, handling over 2,600 daily complaints efficiently. The system’s architecture has been meticulously designed to ensure both **high performance and scalability**, which are essential for managing the large-scale operations of Indian Railways. At the core of the backend infrastructure lies a combination of **Fast API** and **Flask**, two modern web frameworks known for their speed, flexibility, and ease of integration.

**Fast API**, in particular, enables asynchronous processing and rapid API development, allowing for real-time complaint logging, tracking, and status updates. **Flask**, on the other hand, serves as a lightweight and adaptable solution for managing backend services, facilitating seamless integration with databases and frontend interfaces. A critical innovation in this architecture is the use of **Graph SQL (Graph-based Structured Query Language)**, which greatly enhances the system’s ability to retrieve and route complaints based on complex relational data structures. Unlike traditional relational databases, Graph SQL leverages **nodes and edges** to represent entities and their relationships. This structure proves exceptionally beneficial for modeling the intricate web of interconnections between stations, departments, personnel, and types of grievances.

As a result, complaint data can be efficiently traversed and routed to the most appropriate resolution node, significantly reducing the processing time and eliminating redundant manual steps. This scalable and modular design ensures that the system is capable of accommodating the immense volume of activity within Indian Railways, which includes **over 13,000 passenger trains and more than 7,000 stations**. With an average of **2,600 complaints lodged daily**, the system must not only process large amounts of data but also adapt to varying levels of traffic without compromising on speed or accuracy.

The chosen tech stack and data model allow for dynamic scaling, enabling the platform to seamlessly expand in response to increased usage or future enhancements, such as multilingual support, advanced analytics, or integration with additional communication channels. In summary, the combination of high-performance backend frameworks and intelligent data modeling ensures that the system is not only fast and reliable but also robust enough to support the growing needs of a nationwide complaint management platform like **RailMadad**. This positions Indian Railways to deliver a smarter, faster, and more responsive grievance redressal service for millions of passengers across the country.

The proposed AI-driven complaint resolution system for **RailMadad** demonstrates a significant improvement in automating and streamlining the process of passenger grievance redressal within Indian Railways. The implementation of advanced Natural Language Processing (NLP), sentiment analysis, voice recognition, and chatbot technology has not only enhanced the efficiency of complaint handling but has also contributed to a higher degree of user satisfaction through timely and personalized responses.

**5.6 MODEL PERFORMANCE AND ACCURACY**

The experimental evaluation of the model was conducted using a curated dataset comprising 2,694 complaint entries sourced from various social media platforms such as Twitter, Instagram, and Reddit. These complaints were divided into two classes - **emergency** and **non-emergency** to test the system's ability to accurately classify and prioritize issues. Using **BERT** (Bidirectional Encoder Representations from Transformers), a powerful NLP model known for its deep contextual understanding of language, the classification model was trained over multiple epochs. The model achieved an exceptional **accuracy of 95.93%**, with **precision** and **recall** values of 95.94% and 95.93%, respectively. These metrics confirm the model’s ability to minimize both false positives and false negatives, ensuring that critical complaints are flagged appropriately and acted upon without unnecessary delays.

The high **F1-score** of 96.61% further affirms the model's balanced performance across precision and recall. The training process also revealed key insights into the model’s learning behavior. The graph depicting the **loss function’s standard deviation** across training and validation sets indicated a consistent decrease in error without signs of overfitting. This highlights the model's robustness and generalizability to unseen data, a crucial requirement in real-world deployment scenarios where complaint phrasing and tone can vary significantly.

**5.7 MODEL COMPARISON**

The field of Natural Language Processing (NLP) has witnessed a remarkable evolution in its quest to imbue machines with the ability to understand and process human language. From the foundational simplicity of Logistic Regression to the contextual mastery of Bidirectional Encoder Representations from Transformers (BERT), the journey reflects a continuous pursuit of capturing the intricate nuances and sequential dependencies inherent in language.

Examining these models – Logistic Regression, Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), and BERT – reveals a fascinating progression in architectural complexity, contextual awareness, and overall performance in tackling diverse NLP tasks. At the genesis of many NLP applications lies Logistic Regression, a stalwart of statistical modeling. Its strength lies in its simplicity and interpretability. As a linear model, it predicts the probability of a categorical outcome by applying a sigmoid (or softmax for multi-class) function to a weighted sum of input features.

However, its capacity to handle the sequential nature of language is inherently limited. To process text, Logistic Regression necessitates a crucial intermediary step: feature engineering. Techniques like Bag-of-Words, TF-IDF, and even the use of pre-trained word embeddings serve to transform variable-length text into fixed-dimensional numerical vectors. While effective for basic text classification or sentiment analysis on short, relatively context-independent texts, Logistic Regression fundamentally treats each word or n-gram as an isolated entity. It lacks the intrinsic ability to discern the contextual meaning of a word within a sentence or to capture long-range dependencies that often dictate the overall sentiment or meaning. Its interpretability, stemming from the direct correlation between feature weights and the predicted outcome, remains a valuable asset, particularly when understanding the driving factors behind a classification is paramount. Yet, its linear nature ultimately restricts its ability to model the complex, non-linear relationships that characterize human language.

The limitations of handling sequential data in models like Logistic Regression paved the way for the emergence of Recurrent Neural Networks (RNNs). Designed explicitly to process sequences, RNNs introduce the concept of a hidden state, a form of memory that carries information from previous steps in the sequence. At each time step, the RNN processes the current input and the preceding hidden state to generate a new hidden state and an output. This recurrent connection allows the network to consider the history of the sequence, offering a significant step forward in capturing contextual information compared to models that treat each input independently. RNNs found applications in tasks like language modeling, where predicting the next word relies heavily on the preceding sequence, and basic machine translation. However, traditional RNNs encountered a critical bottleneck: the vanishing and exploding gradient problems. As the length of the input sequence increased, the ability of the network to propagate information from earlier time steps diminished, hindering their capacity to learn long-range dependencies. This fundamental challenge limited their effectiveness in tasks requiring the understanding of context spanning longer stretches of text.

To address the shortcomings of traditional RNNs, Long Short-Term Memory Networks (LSTMs) were developed. LSTMs represent a significant architectural innovation, introducing memory cells and intricate gating mechanisms – the input gate, forget gate, and output gate. These gates act as regulators, controlling the flow of information into, out of, and within the memory cell. The forget gate determines what information to discard, the input gate decides what new information to store, and the output gate controls what information from the cell state is exposed to the hidden state. This sophisticated mechanism allows LSTMs to selectively retain relevant information over extended sequences, effectively mitigating the vanishing gradient problem.

Consequently, LSTMs proved remarkably successful in a wide array of NLP tasks demanding the comprehension of long-term dependencies, including advanced machine translation, text generation, and sentiment analysis on longer, more nuanced texts. The advent of Bidirectional LSTMs further enhanced their contextual understanding by processing sequences in both forward and backward directions, enabling the model to consider both preceding and succeeding context for each word.

The most recent paradigm shift in NLP has been spearheaded by Transformer-based models, with BERT as a prominent example. Departing from the sequential processing of RNNs and LSTMs, BERT leverages the Transformer architecture, which relies entirely on the self-attention mechanism. This revolutionary approach allows the model to process the entire input sequence in parallel, directly computing relationships between all pairs of words, irrespective of their distance. The self-attention mechanism enables the model to weigh the importance of different words in the input when encoding a particular word, leading to a deep understanding of contextual relationships.

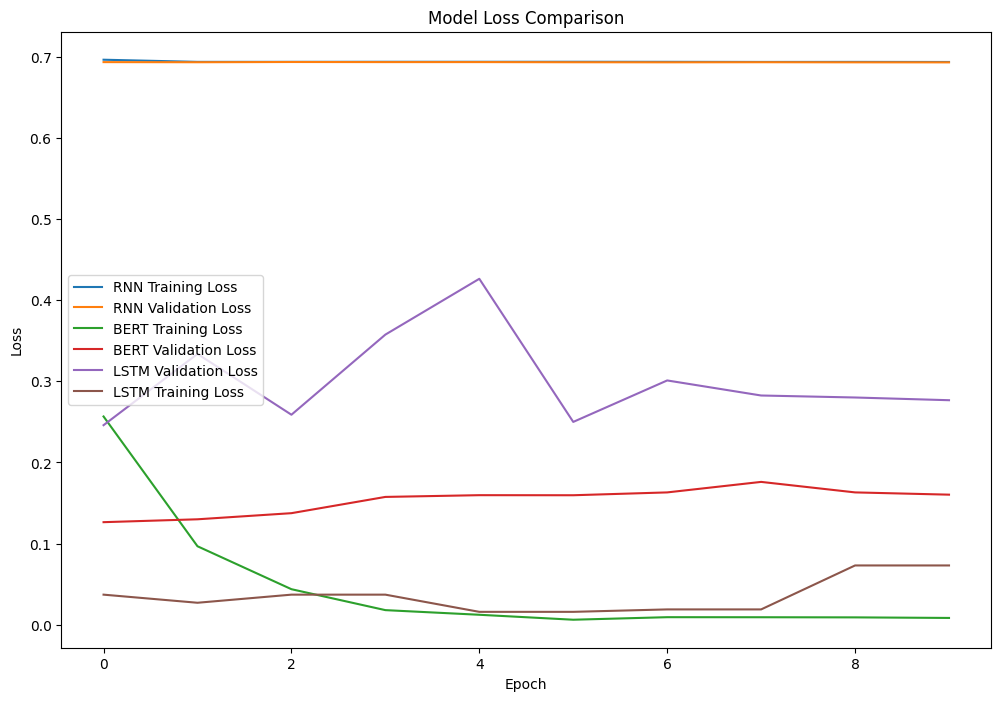
BERT's architecture is characterized by its depth, comprising multiple layers of self-attention mechanisms and feed-forward networks. Its pre-training on massive amounts of unlabelled text data, using tasks like Masked Language Modelling and Next Sentence Prediction, equips it with a rich understanding of language semantics and syntax. Subsequently, BERT can be fine-tuned on specific downstream NLP tasks with relatively smaller task-specific datasets, often achieving state-of-the-art results across a wide spectrum of applications, including text classification, question answering, named entity recognition, and natural language inference. A key innovation of BERT is its generation of contextualized word embeddings, where the representation of a word dynamically changes based on its surrounding context within a sentence, overcoming the limitations of static word embeddings.

**Table 5.3 Model Comparison**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Feature** | **Logistic Regression** | **RNN** | **LSTM** | **BERT** |
| Sequential Data Handling | Limited | Good | Excellent | Excellent |
| Contextual Understanding | Poor | Some | Good | Excellent (bidirectional context) |
| Long-Range Dependencies | No | Struggles (exploding gradients) | Handles well | Handles very well (self-attention) |
| Memory Mechanism | None | Hidden state | Memory cells and gates | Self-attention over the entire sequence |
| Complexity | Low | Medium | High | Very High |
| Training Speed | Fast | Medium | Slow | Very slow (pre-training), Fast (fine-tuning) |
| Typical Use Cases | Simple classification | Language modelling, basic sequence tasks | Complex sequence tasks, long dependencies | Wide range of NLP tasks, state-of-the-art performance |

In conclusion, the evolution from Logistic Regression to BERT represents a remarkable journey in our pursuit of enabling machines to truly understand human language. Logistic Regression, with its simplicity and interpretability, provided a foundational stepping stone. RNNs introduced the crucial concept of sequential processing but were hampered by gradient issues. LSTMs addressed these limitations with sophisticated memory mechanisms, significantly enhancing the ability to capture long-range dependencies.

Finally, BERT, with its parallel processing and self-attention mechanism, has ushered in an era of deep contextual understanding, achieving unprecedented performance across a wide range of NLP tasks. While each model has its strengths and weaknesses, and the choice of model often depends on the specific task and available resources, this progression underscores the continuous innovation and increasing sophistication in our quest to bridge the gap between human language and machine comprehension.

****

**Figure 5.2 Model Comparison**

**A Tale of Performance: Unpacking Accuracy across the NLP Landscape**

The realm of Natural Language Processing (NLP) thrives on the ability of models to accurately decipher and process the complexities of human language. The reported accuracies of 95% for BERT, 49% for RNN, 80% for Logistic Regression, and 90% for LSTM paint a vivid picture of the varying capabilities and architectural nuances of these distinct approaches. These figures, while specific to a particular NLP task and dataset, offer valuable insights into the inherent strengths and limitations of each model in capturing the intricate patterns within textual data.

The standout performer in this comparison is undoubtedly BERT, achieving an impressive accuracy of 95%. This exceptional result is a testament to its revolutionary Transformer-based architecture and its pre-training paradigm. As discussed earlier, BERT's core strength lies in its self-attention mechanism, allowing it to simultaneously consider the relationships between all words in a sequence, irrespective of their distance. This parallel processing of context, coupled with its deep, multi-layered structure trained on vast amounts of text, endows BERT with an unparalleled ability to understand the nuanced, bidirectional context of language.

The high accuracy suggests that the task at hand likely benefited significantly from this deep contextual understanding, where the meaning of a word is heavily influenced by its surrounding words and the overall sentence structure. BERT's pre-trained knowledge, acquired from massive corpora, allows it to generalize effectively to specific downstream tasks, often requiring less task-specific data to achieve remarkable performance. This result underscores BERT's dominance in many complex NLP tasks, showcasing its capacity to capture intricate linguistic patterns that simpler models often miss.

In stark contrast, the RNN model's accuracy of 49% reveals a significant struggle in tackling the given NLP task. While RNNs were designed to process sequential data by maintaining a hidden state, their inherent difficulty in learning long-range dependencies likely played a crucial role in this lower performance. The vanishing and exploding gradient problems, characteristic of traditional RNNs, hinder the effective propagation of information across longer sequences. This limitation would be particularly detrimental in tasks where understanding context spanning multiple words or clauses is essential. The low accuracy suggests that the task might have involved intricate sequential dependencies that the basic recurrent architecture was unable to effectively model. While RNNs laid the groundwork for processing sequential data, their limitations in handling complex, long-range contextual relationships often result in lower performance on more demanding NLP tasks compared to their more advanced successors.

The Logistic Regression model, achieving an accuracy of 80%, occupies an interesting middle ground. As a linear model that typically relies on feature engineering to process text, its performance here suggests that the task likely possessed some linearly separable aspects or that the engineered features (such as TF-IDF or basic word embeddings) captured a significant portion of the discriminatory information. While Logistic Regression lacks the inherent ability to understand word order and deep contextual relationships, it can still perform surprisingly well on tasks where the overall topic or sentiment is strongly indicated by the presence or frequency of certain keywords. Its relatively high accuracy compared to the RNN highlights that for some NLP tasks, especially those with less intricate sequential dependencies, well-crafted features can be surprisingly effective. Furthermore, its simplicity and interpretability can be advantageous in scenarios where understanding the contribution of individual features is important, even if it ultimately sacrifices some performance compared to more complex, context-aware models.

The LSTM model, with an accuracy of 90%, demonstrates a significant improvement over the basic RNN and even surpasses Logistic Regression, coming close to the performance of BERT. This highlights the effectiveness of LSTMs' sophisticated memory cells and gating mechanisms in overcoming the limitations of traditional RNNs. By selectively retaining and forgetting information across sequences, LSTMs excel at capturing long-range dependencies that are crucial for understanding context in many NLP tasks. The 90% accuracy suggests that the task likely benefited from the LSTM's ability to model these longer-term relationships within the text. While BERT's bidirectional context understanding provides a slight edge, the strong performance of the LSTM underscores its continued relevance and effectiveness in handling complex sequential data and capturing nuanced contextual information.

In conclusion, the comparative accuracies of these models offer a compelling illustration of the advancements in NLP. The linear simplicity of Logistic Regression can still yield respectable results when the task allows for effective feature engineering. The basic RNN, while pioneering sequential processing, often struggles with complex dependencies. LSTMs represent a significant leap forward in handling long-range context, achieving high accuracy on many challenging tasks. Ultimately, BERT's Transformer-based architecture and pre-training strategy empower it with the deepest contextual understanding, leading to state-of-the-art performance in a wide array of NLP applications. These results underscore the critical role of architectural design and training methodologies in enabling models to effectively decipher the intricate tapestry of human language.

**CHAPTER 6**

**CONCLUSION AND FUTURE WORK**

In an era that demands efficient and inclusive public services, Indian Railways’ integration of Artificial Intelligence into the RailMadad grievance redressal system marks a strategic and transformative step. This initiative redefines passenger engagement by incorporating cutting-edge technologies such as Natural Language Processing (NLP), speech recognition (Whisper), sentiment analysis, AI-driven chatbots (RAG), and graph-based routing (Graph SQL).

The AI-enhanced RailMadad enables real-time complaint registration via text and voice, with automatic categorization using BERT and intelligent routing ensuring swift redressal. A multilingual, voice-supported chatbot delivers 24/7 support, boosting transparency, accessibility, and user satisfaction across India’s diverse demographic. By automating functions like classification, emergency detection, and task allocation, the system significantly reduces human error and improves efficiency.

Railway officials benefit from real-time dashboards and analytics, empowering data-driven decision-making and long-term service optimization. Despite challenges such as regional language diversity, infrastructure needs, and data privacy concerns, the platform demonstrates scalability and resilience, handling thousands of daily complaints seamlessly.

Future enhancements may include predictive analytics, image/video input handling, sentiment heatmaps, and integration with national digital platforms like Aadhaar and DigiLocker. These advancements promise to further modernize grievance management and make the system even more inclusive and intelligent.

Ultimately, the AI-powered RailMadad platform is not just a technical upgrade—it represents a paradigm shift in how large public institutions can use AI to deliver smarter, more compassionate, and citizen-centric services.

**REFERENCES**

[1] Dubey, P. K., & Solanki, G., “RailMadad Grievance Redressal Mechanism for Better Services to Rail Passengers”, International Journal of Food and Nutritional Sciences, vol.11(11), pp.112-117, 2018.

[2] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I., “Attention Is All You Need”, NeurIPS, vol.30, pp.5998–6008, 2017.

[3] Sun, C., Qiu, X., Xu, Y., & Huang, X., “How to Fine-Tune BERT for Text Classification”, arXiv preprint, arXiv:1905.05583v3, 2020.

[4] Jamshidi, S., Mohammadi, M., Bagheri, S., Najafabadi, H. E., Rezvanian, A., & Gheisari, M., “Effective Text Classification Using BERT, MTM-LSTM and Decision Trees”, Data & Knowledge Engineering, vol.151, 2024.

[5] Miller, S. J., & Wang, L., “Multi-Modal Classification Using Images and Text”, SMU Data Science Review, vol.3(3), 2020.

[6] Huang, F., Zhang, X., Zhoa, Z., Xu, J., & Li, Z., Image–Text Sentiment Analysis via Deep Multimodal Attentive Fusion. Information Fusion, vol.57, pp.13–22, 2020.

[7] Vinnarasu, A., & Jose, D. V., Speech to Text Conversion and Summarization for Effective Understanding and Documentation. International Journal of Electrical and Computer Engineering (IJECE), vol.9(5), pp.3642–3648, 2019.

[8] Radford, A., Kim, J. W., Xu, T., Brockman, G., McLeavey, C., & Sutskever, I., Robust Speech Recognition via Large-Scale Weak Supervision. arXiv preprint, arXiv:2212.04356, 2022.

[9] Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., & Riedel, S., Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks. NeurIPS, vol.33, pp.9459–9474, 2020.

[10] Tian, Y., The World of Graph Databases from an Industry Perspective. arXiv preprint, arXiv:2211.13170, 2022.

[11] Besta, M., Gergstenberger, R., Fischer, M., Podstawski, M., Barthels, C., Alonso, G., & Hoefler, T., Demystifying Graph Databases: Analysis and Taxonomy of the Data Organization, System Designs and Graph Queries. arXiv preprint, arXiv:1910.09017v8,2023.

[12] Huang, W., Hew, K. F., & Fryer, L. K., Chatbots for Language Learning: A Systematic Review. Journal of Computer Assisted Learning, vol.38(1), pp.1–15,2021.

[13] Rapp, A., Curti, L., & Boldi, A., The Human Side of Human-Chatbot Interaction: A Systematic Literature Review. International Journal of Human-Computer Studies, vol.151, pp.102630, 2021.