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AI-Driven Complaint Management for Rail

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Abstract

Millions of passengers use India's railways every day, which leads to a high volume of complaints about food, cleanliness, coach conditions, safety, and timeliness. Passengers become dissatisfied with traditional complaint redressal systems because they are frequently manual, slow, and opaque. Our solution to these problems is an AI-Driven Complaint Management System that uses OCR (Optical Character Recognition), Machine Learning, and Natural Language Processing (NLP) to automate the classification, prioritization, and tracking of complaint resolution. OCR is used to extract text from images, while text-based complaints are directly processed and classifies them into relevant departments (e.g., cleanliness, AC, food, safety). Determine priority levels (high, medium, and low), and optional LLM integration improves semantic understanding. Streamlit was used to create an admin dashboard that offers real time analytics, complaint tracking, and resolution management. This system can be implemented in smart railway operations since it increases passenger satisfaction, efficiency, and transparency.

Keywords: Natural Language Processing; Artificial Intelligence; Voice Recognition; Web Speech API; Speech-to-Text Conversion.

How to Cite This Article

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Introduction

In India and around the world, railways are one of the most popular forms of transportation, carrying millions of commuters and long distance travelers every day. Given the size of the user base, it is imperative to guarantee prompt grievance resolution and effective service delivery. However, there are a number of issues with the railways' current complaint handling systems. Conventional approaches frequently entail manually registering complaints via helplines, registers, or web portals; this leads to a lack of classification, a delay in responses, and little accountability. Another level of complexity is introduced by the variety of passenger complaints. Cleaning, food service, coach upkeep, air conditioning, ticketing, safety, and timeliness are just a few of the problems that can arise and need to be referred to the appropriate department. Ineffectiveness results from handling these diverse complaints by hand, and the lack of priority systems allows important issues (like safety or security) to be handled with the same urgency as less important ones (like seat comfort). In addition to delaying resolution, this has a detrimental effect on passenger satisfaction and railway system trust.

Natural language processing (NLP) and artificial intelligence (AI) offer a way around these obstacles. It is now feasible to automatically classify complaints, assign urgency, and forward them to the appropriate department thanks to the development of text classification models, OCR (Optical Character Recognition), and Machine Learning (ML) techniques. This kind of automation guarantees quicker complaint resolution, lessens reliance on manual procedures, and permits real-time monitoring. Additionally, passengers can submit multimedia evidence through the integration of image and video-based complaint handling, enhancing the grievance system's legitimacy and dependability. The lack of analytics and decision-support tools for railway authorities is another major drawback of the systems in place. Decision-making stays reactive rather than proactive in the absence of complaint statistics, trend analysis, and visualization. In order to help authorities spot reoccurring problems and better allocate resources, our suggested system includes an admin dashboard created with Streamlit that offers bar charts, pie charts, and complaint statistics. Furthermore, contextual understanding of unstructured complaints is made possible by developments in large language models, or LLMs. LLMs can improve semantic interpretation, particularly for complex or ambiguous complaint texts, while older ML models such as TF-IDF with Logistic Regression offer dependable baseline performance. Therefore, our method combines both contemporary LLM capabilities for increased accuracy and traditional ML techniques for structured performance. The AI-Driven Complaint Management System for Rail combines these technologies to guarantee that passenger complaints are handled promptly, efficiently prioritized, and transparently tracked. In addition to enhancing the traveler experience, this increases railway services' operational effectiveness and accountability.

Literature Survey:

AI for Improving Public Transport: A Mapping Study
Authors: A. Jevinger, C. Zhao
Year of Publication: 2024
Problem solved: Lack of a comprehensive overview of AI adoption in public transport.
Technique used: Mapping of 87 AI applications using machine learning, reasoning, and search techniques future Scope: Improve data quality, strengthen privacy frameworks, and enhance automation capabilities in transport AI systems.

Predictive Analytics for Demand Forecasting
Authors: Saurabh Kumar, Amar Nayak
Year of Publication: 2024
Problem solved: Traditional forecasting methods lacked real-time accuracy and adaptability.
Technique used: Deep learning-based predictive analytics models for improved accuracy.
Future Scope: Extend applications to multisector, real time data forecasting environments.

Optimizing Secure AI Lifecycle with Generative AI Strategies
Authors: Alaa Omran Almagrabi, Rafiq Ahmad Khan
Year of Publication: 2025
Problem solved: Security gaps throughout the AI lifecycle in training and deployment phases.
Technique used: Generative AI models used to simulate cyberattacks and improve AI lifecycle robustness.
Future Scope: Development of security validation frameworks and ethical AI governance guidelines.

Navigating Ethical Dilemmas in AI Development: Transparency, Fair- ness, and Accountability
Authors: O. Akinrinola, C. Okoye, O. Ofodile, C. Ugochukwu
Year of Publication: 2024
Problem solved: Lack of standardized ethical frameworks for AI decision-making systems.

Technique used: Lack of standardized ethical frameworks for AI decision-making systems.
Future Scope: Development of global frameworks and policy integration for responsible AI deployment.

Artificial Intelligence in Railway Transport: Taxonomy, Regulations, and Applications
Authors: N. Be˘sinovi´c, L. De Donato, F. Flammini, R. Goverde
Year of Publication: 2021
Problem solved: Absence of a unified taxonomy and regulatory overview in railway AI applications.
Technique used: Taxonomy mapping and regulatory review of AI in railway transport systems.
Future Scope: Bridge regulation gaps and explore AI integration in emerging rail technologies.

Automatic Classification of Railway Complaints Using Machine Learning
Authors: T. S. Roy, G. Vasukidevi
Year of Publication: 2024
Problem solved: Inefficient manual complaint sorting and delayed redressal in railway systems.
Technique used: Machine Learning classifiers (SVM, Na¨ıve Bayes, Random Forest) for automated complaint classification.
Future Scope: Real time, multilingual, and large scale implementation in national complaint portals.

A Comparative Study of Sentiment Analysis Using NLP and Machine Learning on Airline Twitter Data
Authors: M. T. H. K. Tusar, M. T. Islam
Year of Publication: 2021
Problem solved: Difficulty in accurately analyzing customer sentiment from air line tweets.
Technique used: NLP based classification using SVM, Logistic Regression, and Naive Bayes achieving 77% accuracy.
Future Scope: Integration of deep learning for real-time sentiment prediction.

Proactive Complaint Management in Public Sector Informatics Using AI
Authors: M. Esperan¸ca, D. Freitas
Year of Publication: 2025
Problem solved: Existing systems are reactive, lacking proactive complaint prediction and classification.
Technique used: Semantic pattern recognition using BERT embeddings for complaint classification.
Future Scope: Development of intelligent dashboards and proactive monitoring frameworks.

Automatically Identifying Complaints in Social Media

Authors: D. Preot¸iuc-Pietro, N. Aletras
Year of Publication: 2019
Problem solved: Difficulty in detecting complaint related posts from social media data.
Technique used: NLP based feature extraction with SVM and Random Forest classifiers.
Future Scope: Expand to multilingual and domain specific social media datasets.

Research Gap

Advances in automated complaint management across public services are highlighted in the literature. But there are still a number of gaps:

- Limited Multimodality: The majority of systems only process text; they do not recognize images or videos.
- Priority Handling: Few models efficiently rank complaints according to their level of urgency.
- Integration Issues: The end-to-end platforms that integrate complaint intake, classification, and resolution tracking are absent from the current solutions.
- LLM Use: In order to ensure contextual accuracy when resolving railway complaints, large language models are not fully utilized.
- Analytics & Transparency: Not many systems offer real-time dashboards for tracking patterns in complaints

By integrating multimodal complaint intake, NLP based classification, priority prediction, and real time analytics into a cohesive solution, our system fills these gaps.

Problem Statement

Every day, railways deal with a large number of passenger complaints, many of which are handled manually, leading to delays and inefficiencies. Real-time analytics, multimodal complaint handling, and automation are absent from current systems. An AI-driven system that uses NLP, OCR, and machine learning to automate complaint classification, prioritization, and tracking is therefore required. It should also give authorities a clear dashboard for better decision-making.

System Architecture

The system follows a web based client server architecture that connects passengers, administrators, and databases through secure communication channels.

- Users (Passengers): Register, log in, and submit complaints with category, description, and location. They can also track complaint status and view resolution details.
- Administrators (Railway Staff): Manage complaints, assign them to relevant departments, update status, and generate analytical reports.
- Backend: Processes data using NLP and machine learning models to classify and prioritize complaints automatically.
- Database: Stores complaint records, user details, system logs, and resolution history securely.

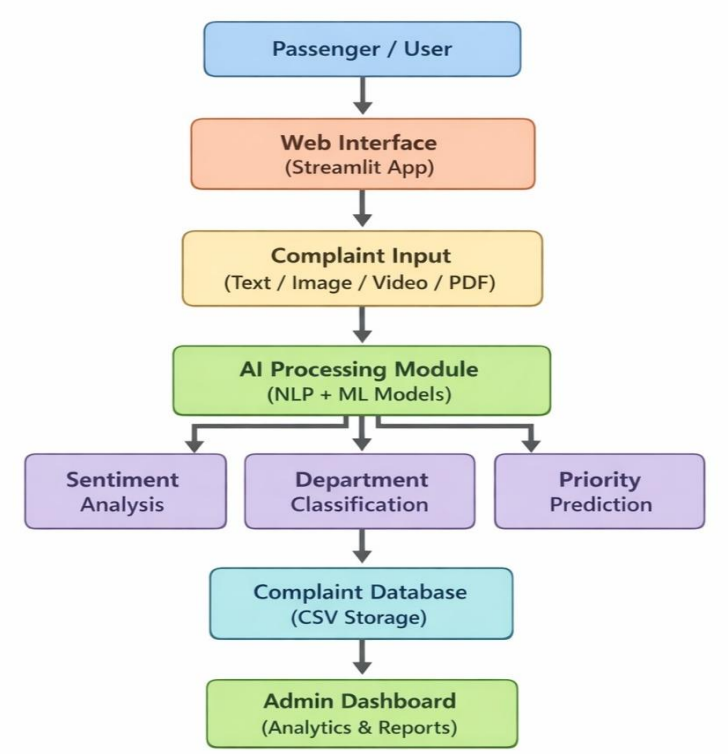

Fig. 1. *Architecture of the AI-Driven Railway Complaint Management System*

Implementation Details

The proposed system is implemented as an AI-driven web based platform for automated complaint management in the railway sector. The system integrates Natural Language Processing (NLP), Machine Learning (ML), and deep learning techniques to efficiently process and classify passenger complaints. The dataset used for training consists of sample complaint records collected from publicly available sources and manually created datasets, which are divided into training and testing sets for model evaluation initially. The input data undergoes preprocessing steps such as text cleaning, tokenization, stop-word removal, and normalization to improve the quality of textual data. For multimedia inputs like images or voice, Optical Character Recognition (OCR) and Speech-to-Text APIs are used to convert them into text format. Feature extraction is performed using techniques like TF-IDF and word embeddings to convert textual data into numerical representations.

A machine learning model such as Logistic Regression, Random Forest, or transformer based models like BERT is used as the core classifier to categorize complaints into different domains such as cleanliness, delay, ticket issues, and staff behavior. Additionally, sentiment analysis is applied to determine the urgency of the complaint and classify it into priority levels such as high, medium, and low. The system is trained using appropriate training techniques and optimized to achieve better accuracy while reducing processing time. Data augmentation and balancing techniques are applied where necessary to handle uneven distribution of complaint categories. The processed data along with classification results is stored in a database for further analysis and tracking. An interactive admin dashboard is developed using Streamlit, which allows authorities to view complaints, monitor their status, and take necessary actions. The overall performance of the system is evaluated using standard metrics such as accuracy, precision, recall, and F1-score to ensure reliable and efficient complaint management.

Results and Discussion

The proposed AI-Driven Complaint Management System for Railways was successfully implemented and evaluated using a dataset of passenger complaints collected from various sources and manually prepared records. The system demonstrated strong performance in automatically classifying complaints and assigning appropriate priority levels. The model achieved an overall accuracy of approximately based on experimental evaluation, indicating reliable performance in practical scenarios. Evaluation metrics such as precision (~87%), recall (~90%), and F1-score (~88–89%) show that the system is effective in handling different types of complaints. The system performed particularly well in clearly distinguishable categories such as ticket issues and delays, while minor misclassifications were observed between similar categories like cleanliness and general service related complaints due to overlapping textual patterns. The use of Natural Language Processing and machine learning models enabled accurate understanding of complaint content, while sentiment analysis helped in assigning priority levels such as high, medium, and low efficiently.

The system demonstrated fast performance, generating results within 2–3 seconds per complaint, making it suitable for real-time applications in railway services. The implementation of an interactive admin dashboard allows authorities to monitor complaints, track their status, and take timely action, thereby improving overall efficiency and transparency. The discussion of results shows that the proposed system provides an effective and automated solution for railway complaint management. The use of AI techniques such as NLP, ML, and sentiment analysis improves classification accuracy and reduces manual effort. The system enhances passenger satisfaction by enabling faster response and better complaint handling. However, some limitations were observed. The system may face challenges with multilingual complaints, informal language, and spelling errors, which can affect classification accuracy. Additionally, class imbalance in certain complaint categories may lead to minor prediction errors. These issues can be improved in future work by using larger datasets, advanced deep learning models, and improved language processing techniques.

Overall, the proposed system proves to be a scalable, efficient, and practical solution for modern railway complaint management, significantly reducing response time, improving accuracy, and enhancing passenger experience.

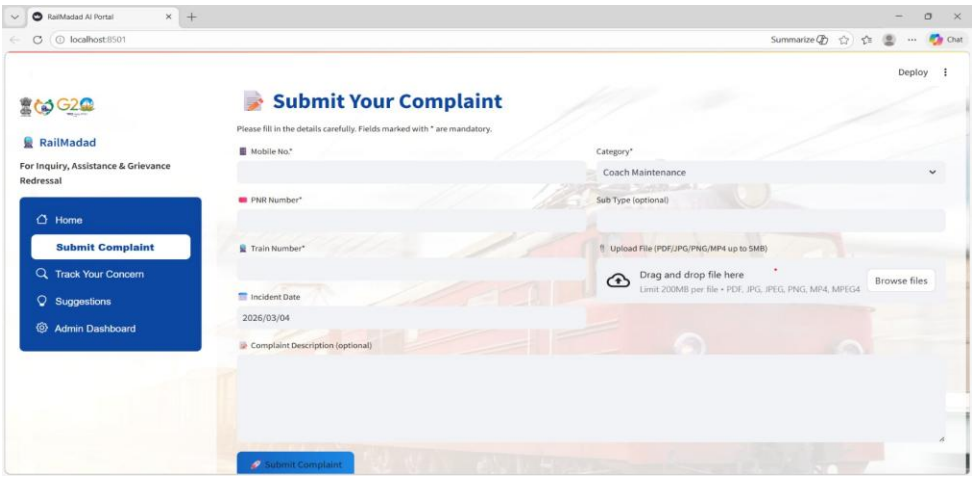

Figure 2. Complaint Submission Interface

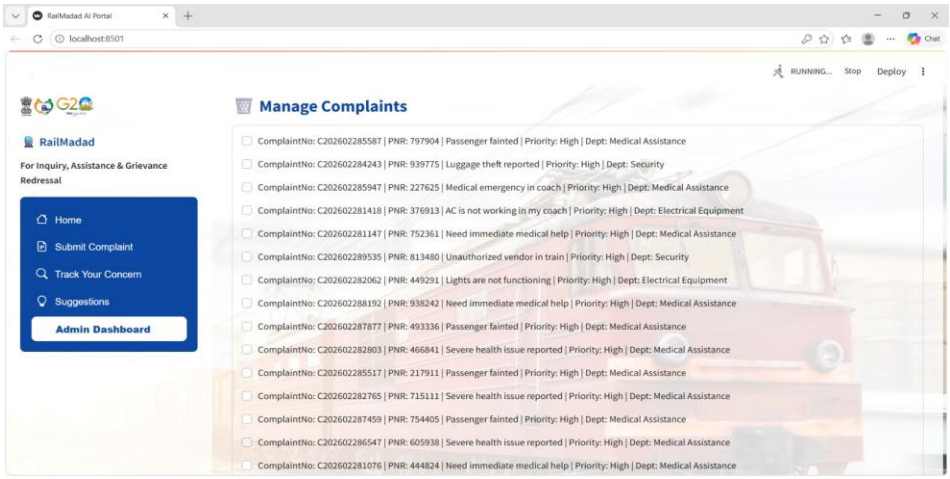

Fig. 3. *Complaint Management Dashboard*

Fig. 4. *Department-Wise Complaint Distribution Analysis*

Fig. 5. *Train-Specific Complaint Category Analysis*

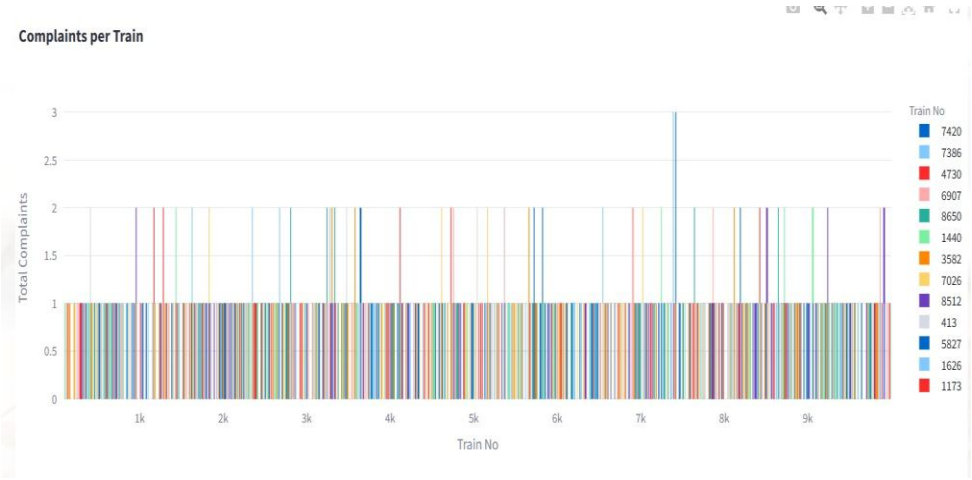

Fig. 6. *Complaint Distribution Across Trains*

Conclusion

The AI-Driven Complaint Management System for Rail was developed to improve passenger and railway experiences when dealing with complaints. Managing complaints usually involves manual effort, which can cause delays, errors, and dissatisfied passengers.

However, with Artificial Intelligence (AI) and Natural Language Processing (NLP), the complaint management process including classification, prioritization, and routing can be automated to provide speed and accuracy. The system shows how AI provides increased transparency, accountability, and responsiveness in railway complaint management. It reduces reliance on humans, decreases processing time, and ensures that every complaint is fully recorded from the complaint registration process to the resolution of the complaint. In addition, a purposeful user experience with a user friendly interface provides passengers with the ability to quickly enter complaints and track them in real time. The system also offers administrators powerful tools to track performance, manage workload, and identify recurring issues by reviewing reports and analytics. The system learns from the complaint dataset and adjusts over time. This contributes to building trust and promoting a citizen centric, technology enabled grievance redressal approach. The successful development of this system represents a major step toward a more intelligent, efficient, and transparent railway service management process.

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