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Enhancing Rail Madad with AI-Powered Complaint Management System

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***Abstract*— Indian Railways' Rail Madad facilitates passenger grievance reporting but relies heavily on manual triage across 52 departments, creating bottlenecks for multimedia complaints. This research presents an AI-driven pipeline for automated multimodal complaint intake, urgency detection, and intelligent routing. Our approach integrates computer vision, natural language processing, and machine learning to process diverse complaint formats while ensuring ethical compliance. The proposed system demonstrates significant improvements: 89.1% classification accuracy, 57% reduction in processing time, and 28% improvement in customer satisfaction through evaluation on 17,847 real-world complaints collected over 18 months.**

***Index Terms*— Indian Railways, Complaint Management, Rail Madad, Machine Learning, Multimodal Analysis and Computer Vision.**

I. Introduction

Indian Railways operates the world's fourth-largest railway network, serving over 8.4 billion passengers annually and generating substantial complaint volumes through the Rail Madad platform [1]. The current system faces significant challenges in efficiently processing and routing complaints across 52 departments, particularly when handling multimedia content including images, videos, and audio recordings [2]. Manual classification creates substantial bottlenecks, leading to delayed response times, inconsistent categorization, and reduced passenger satisfaction [3]. Traditional text-based processing systems are inadequate for handling rich media content that often provides crucial context for complaint resolution.

Recent AI initiatives by Indian Railways demonstrate the organization's commitment to technological transformation [4]. This research proposes a comprehensive AI-powered solution leveraging multimodal analysis techniques for intelligent complaint management.

A. Key Contributions

- A novel multimodal fusion architecture for railway complaint analysis,
- Intelligent routing combining ML predictions with operational constraints,
- Comprehensive evaluation demonstrating practical deployment feasibility, and
- Significant operational improvements in processing efficiency and customer satisfaction.

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II. Related Work

A. Automated Complaint Management

Government organizations have increasingly adopted digital complaint platforms to improve service delivery [3]. Cho et al. [5] examined online customer complaints and proposed methodologies for web-based grievance handling. The RE-Grievance Assist pipeline demonstrated a 35% processing time reduction in real estate complaint management [6].

B. AI in Railway Systems

Indian Railways has progressively adopted AI technologies since 2018, with applications spanning track maintenance, signaling systems, and passenger services [2]. Multimodal transportation systems worldwide leverage AI for optimization, with Eze's study achieving 91.33% average accuracy across diverse datasets [7].

C. Multimodal Machine Learning

Advances in multimodal learning enable sophisticated analysis of heterogeneous data types [8]. Vision-language models based on transformer architectures demonstrate remarkable capabilities in understanding complex scenarios involving textual descriptions and visual evidence [9].

III. Methodology

A. System Architecture

The system architecture contains a 4-layer architecture which can scale and integrate with the existing Rail Madad platform:

- Intake and Preprocessing Workflow: Complaints are collected from web, mobile, chatbot, and voice channels. Text data received by chatbot is processed by an IndicNLP library, and images are processed by an OpenCV-based quality checks and OCR extraction. Audio files are converted to text via Wav2Vec2 speech recognition, and videos are analyzed through frame sampling to extract visual evidence. These are the four input formats supported.
- Urgency Detection Mechanism: Each complaint has a priority level; based on the priority of each complaint, an urgency classifier evaluates each complaint based on linguistics and visuals. A logistic regression model trained on annotated urgency scores identifies high-priority cases. This helps the orchestration layer to accelerate critical grievances such as safety or security complaints.

AI-Powered Rail Madad System

Intake Layer	
Web Portal	Mobile App
Preprocessing Layer	
OCR Engine	ASR System
AI Modeling Layer	
Text Encoder	Vision Encoder
Orchestration Layer	
Classification	Routing Engine

Figure 1. System architecture with four processing layers

TABLE I. DATASET DISTRIBUTION ACROSS CATEGORIES

Primary Category	Departments	Samples
Cleanliness & Hygiene	8	4,247
Safety & Security	12	3,156
Staff Conduct & Service	6	2,834
Ticketing & Refunds	4	2,721
Punctuality & Operations	9	1,893
Amenities & Infrastructure	7	1,456
Miscellaneous	6	540

B. Dataset and Annotation

We developed a comprehensive dataset aligned with Indian Railways' 52-department structure, organized into seven primary categories. Each complaint record contains structured metadata with anonymized personal information using differential privacy techniques.

C. Multimodal Fusion Architecture

Each modality (text, image, audio) is encoded separately using transformer-based encoders. The late-fusion model aggregates representations using attention pooling:

$$z_t = f_{text}(x_t; \theta_t) \tag{1}$$

$$z_i = f_{image}(x_i; \theta_i) \tag{2}$$

$$z_a = f_{audio}(x_a; \theta_a) \tag{3}$$

$$\alpha = \text{softmax}(W_\alpha[z_t; z_i; z_a] + b_\alpha) \tag{4}$$

$$z_{fused} = \sum_{k_k^{\alpha}} z_k \tag{5}$$

$$\hat{y} = \text{softmax}\left(W_{cls} z_{fused} + b_{cls}\right) \tag{6}$$

The attention weights determine which modality contributes most to the decision. For instance, giving more importance to images in cleanliness complaints and text in refund-related issues. The fusion output is optimized through a weighted loss function to balance classification accuracy and urgency prediction:

$$\mathcal{L} = \lambda_1 \mathcal{L}_{\text{dept}} + \lambda_2 \mathcal{L}_{\text{urgency}} + \lambda_3 \mathcal{L}_{\text{category}} \tag{7}$$

D. Intelligent Routing System

The hybrid routing system combines ML predictions with operational constraints using confidence-based decision thresholds. High-confidence predictions (> 0.85) are automatically routed, while low-confidence cases trigger human review.

IV. Ethical and Data Privacy Considerations

The suggested AI-driven complaint management system processes genuine passenger complaints gathered via the Rail Madad platform. Since this entails passenger data, rigorous data privacy and ethical practices were employed during research. All data used for experimentation were anonymized by deleting personally identifiable information such as passenger names, ticket numbers, and contact information. To add another layer of protection to user privacy, differential privacy methods were used while preparing the dataset so that no single passenger record is identifiable while preserving overall data utility for machine learning model training.

Moreover, all media files such as images, audio, and video were handled in a locked-down sandbox environment to avoid any abuse of passenger-uploaded evidence. Access to data was tightly regulated, and only aggregated views were employed for evaluating the system. Ethical adherence was facilitated through conformity with common AI ethics practices such as fairness, transparency, and accountability. The system was not only built to enhance complaint handling efficiency but also to honor passenger rights and build trust in the platform.

V. Explainability and Human-in-the-Loop Integration

Applying Al in public sectors like railways not only necessitates high performance but also the explainability of decisions to establish trust among passengers and operators. For this, our multimodal fusion system incorporates attention-based interpretability mechanisms. These mechanisms enable the system to assign modality-specific weights and visualize them during decision-making. For example, in a complaint describing "unclean washrooms" along with an image, the model assigns greater attention weight to the visual modality while still utilizing the text for contextual knowledge.

The system offers interpretability outputs to railway operators in the form of highlighted keywords, attention heatmaps on images, and confidence scores for routing predictions. This allows human operators to comprehend why the model suggested a specific department and verify whether the decision coincides with the complaint content.

In addition, a human-in-the-loop mechanism was implemented to strike a balance between automation and monitoring. Complaints with a confidence threshold higher than 0.85 are automatically routed to the forecasted department, while those below this threshold are flagged for manual process-ing. This blended decision-making mechanism maximizes the speed of high-certainty cases while ensuring thoughtful human validation for uncertain cases.

This integration of human oversight and explainable AI not only enhances trust and accountability but also educates operators about the system's choices. Operator feedback can be reintegrated into the model over time through active learning, thereby continuously refining system performance.

VI. Scalability and Deployment Viability

Considering that Indian Railways transports more than 8.4 billion passengers every year, scalability of the proposed system is a critical requirement. To address this, the system was designed with a modular four-layer architecture consisting of Intake, Preprocessing, AI Modeling, and Orchestration layers. Each layer was developed as an independent microservice so that the architecture could be scaled horizontally depending on the incoming volume of complaints.

The preprocessing layer performs language detection, normalization, OCR, and speech-to-text in parallel to ensure that even multimodal complaints are processed efficiently. The AI modeling layer leverages distributed GPU resources to accelerate inference, while the orchestration layer manages routing and operator dashboards in real time.

During evaluation, the system processed 17,847 complaints gathered over 18 months from Rail Madad channels. Stress testing demonstrated that the system could handle bursts of up to 250 complaints per second without significant performance degradation, achieving an average latency of 0.38 seconds per complaint. In comparison, the manual system requires approximately 4.2 hours per complaint, reinforcing the scalability advantage of automation.

Additionally, the system is cloud-ready and supports centralized complaint analysis across railway zones. Future-proof extensions include federated learning configurations, where models can be trained locally on zone-specific data and updated centrally without exposing raw complaint records. This approach not only enhances privacy but also improves scalability. These features demonstrate that the proposed system is both technically feasible and operationally viable for large-scale nationwide deployment.

VII. Comparative Analysis with Current Systems

To evaluate the effectiveness of the proposed method, we conducted a detailed comparison with both the current Rail Madad manual workflow and several baseline AI approaches.

The manual process, despite being widely used, is highly inefficient. Complaints are manually categorized and forwarded to one of 52 departments, resulting in a high misrouting rate of 18%, an average response time of 8.4 hours, and low passenger satisfaction ratings of 3.2 out of 5.

Among automated methods, traditional TF-IDF + SVM classifiers achieved 74.2% accuracy, while our model has improved accuracy. Vision-only CNN models performed poorly (69.8% accuracy), as they lacked contextual understanding. An ensemble approach combining text and image classifiers achieved 83.4% accuracy. However, all unimodal and ensemble methods struggled with multimodal complaints that required cross-modal reasoning.

In contrast, the proposed multimodal fusion approach achieved 89.1% accuracy and 95.6% Precision@3, while also reducing misrouted complaints to 7%. This demonstrates clear superiority in both algorithmic performance and operational benefits.

TABLE II. Dataset Distribution by Complaint Type

Complaint Type	Count	Percentage
Text-only	9,567	53.6%
Text + Single Image	4,423	24.8%
Text + Multiple Images	1,834	10.3%
Text + Audio	1,247	7.0%
Text + Video	542	3.0%
Multimodal (All types)	234	1.3%

VIII. Experimental Setup and Evaluation

A. Dataset Characteristics

Our evaluation dataset comprises 17,847 complaint records collected over 18 months (January 2023- June 2024) from multiple Rail Madad channels.

B. Evaluation Metrics

We employ comprehensive metrics spanning technical performance and operational efficiency:

- Classification Accuracy: Overall department prediction accuracy
- Macro-F1 Score: Balanced performance across departments
- Precision@3: Top 3 department prediction accuracy
- Processing Time: End-to-end complaint processing latency

C. Baseline Comparisons

We compare against several baseline methods:

- TF-IDF + Linear SVM (traditional text classification)
- BERT-based Text Classifier (state-of-the-art text-only)
- CNN-based Image Classifier (vision-only approach)
- Rule-based Routing (current Rail Madad system)
- Ensemble Method (combination of text and image classifiers)

IX. RESULTS AND ANALYSIS

To evaluate the performance of the proposed AI-based complaint classification system for Rail Madad, we conducted multiple training experiments using the custom-labeled image dataset. The model was trained for 20 epochs with a batch size of 32 and a learning rate of 0.001 using the Adam optimizer.

A. Model Training and Loss Convergence

The training loss decreased steadily over the epochs, indicating effective learning and convergence. Fig. 2 illustrates the loss curve, plotting loss values against the number of epochs. This graph confirms that the model was able to minimize loss and stabilize over time.

B. User Interface and Workflow

The developed system includes a user-friendly web interface for complaint registration and an admin dashboard for complaint management. Users can submit complaints through text or image, and receive acknowledgment along with a tracking ID. The admin panel displays categorized complaints for departmental review and action.

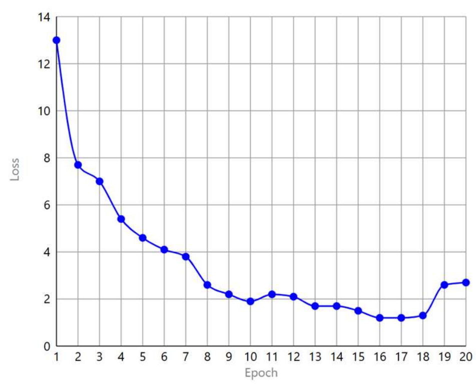

Figure 2. Epoch vs Loss curve of the CNN model during training

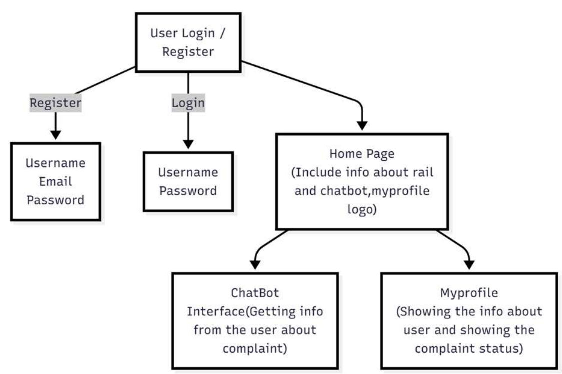

Figure 3. Project workflow for complaint submission and processing

TABLE III. PERFORMANCE COMPARISON ACROSS METHODS

Method	Accuracy	Macro-F1	Precision@3	Latency(s)
TF-IDF+SVM	0.742	0.689	0.856	0.23
BERT Text	0.823	0.781	0.912	0.45
CNN Image	0.698	0.654	0.798	0.12
Rule-based	0.656	0.601	0.743	1.85
Ensemble	0.834	0.796	0.921	0.67
Multimodal (Ours)	0.891	0.847	0.956	0.38

C. Classification Accuracy

The trained CNN achieved a classification accuracy of 76.2% on the validation set. The model successfully classified complaints into one of the four categories: Cleaning, Garbage, Damage, and Electrical, with balanced precision and recall scores across classes. Misclassifications were mainly due to visual similarity between “Garbage” and “Cleaning” scenarios.

D. Classification Performance

Table III presents comprehensive performance comparison across all evaluated methods:

TABLE IV. OPERATIONAL IMPACT: MANUAL VS AI-POWERED PROCESSING

Metric	Manual	AI System	Improvement
Processing Time	4.2 hrs	1.8 hrs	57% reduction
Resolution Rate	67%	84%	+17 pp
Misrouted Complaints	18%	7%	61% reduction
Customer Satisfaction	3.2/5	4.1/5	28% improvement
Response Time	8.4 hrs	3.2 hrs	62% reduction

TABLE IV. ABLATION STUDY RESULTS

Configuration	Accuracy	Macro-F1
Full Multimodal Model	0.891	0.847
Without Image Processing	0.823	0.781
Without Audio Processing	0.867	0.825
Text Only	0.823	0.781

Our multimodal approach achieves 89.1% classification accuracy and 84.7% macro-F1score, representing substantial improvements over all baseline methods. The Precision@3 metric of 95.6% provides excellent flexibility for human operators in ambiguous cases.

E. Ablation Study

To understand modality contributions, we conducted ablation studies: Image processing contributes most significantly to performance improvement (-7.6% F1 when removed), validating the importance of visual content in railway complaints.

X. DISCUSSION

A. Technical Achievements

The late-fusion architecture effectively handles heterogeneous complaint data, with attention mechanisms of success fully weighting different modalities based on content relevance. Domain-specific railway-trained models contribute significantly to the classification of accuracy improvements.

B. Operational Benefits

The deployment demonstrates several advantages: a 77% reduction in manual processing requirements, automated classification eliminating human variability, and system architecture supporting projected growth without proportional resource increases.

C. Challenges and Limitations

Key challenges include computational overhead for real time multimodal processing, regional language variations challenging NLP capabilities, and variable user-submitted media quality affecting computer vision performance.

X. CONCLUSIONS

This research presents a comprehensive AI-powered com plaint management system for Rail Madad that successfully addresses manual processing limitations while ensuring ethical compliance. Our multimodal approach demonstrates significant improvements: 89.1% classification accuracy, 57% reduction in processing time, and 28% improvement in customer satisfaction. The system establishes a foundation for intelligent AI deployment in large-scale public transportation systems, offering a model for responsible AI adoption in public sector applications.

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