JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Online chatbot based ticketing system

Edwin Dhas p[1], Aishwarya P[2], Gopi Selvi D[3], Joice Britto J[4], Usha P[5]
Department of Computer Science and Engineering
Anna University

Abstract

The Railway Chatbot is an intelligent by providing real-time information and services related to train schedules, ticket bookings, PNR status, and more. This chatbot leverages advanced Natural Language Processing (NLP) techniques, specifically BiLSTM (Bidirectional Long Short-Term Memory), to understand and process user queries in a highly efficient and context-sensitive manner. By using NLP techniques such as tokenization, part-of-speech tagging, and named entity recognition (NER), the chatbot can extract key information from user input and offer relevant, accurate responses. The BiLSTM model is trained on a large dataset of historical train-related queries and responses, enabling it to learn the nuances of passenger queries and improve over time.

Keywords - Railway Chatbot, Natural Language Processing (NLP), Bidirectional Long Short-Term Memory (BiLSTM), Named Entity Recognition (NER), Tokenization, Passenger Assistance System, Train Schedule Information, Real-time Query Processing, Deep Learning, Context-sensitive Response

Introduction

The increasing reliance on railway transport necessitates the provision of efficient, real-time assistance to passengers for activities such as train schedule inquiries, ticket bookings, and PNR status updates. Traditional information systems often fall short in meeting the dynamic and personalized needs of users. To address these challenges, intelligent conversational agents have emerged as a viable solution, offering interactive, scalable, and user-friendly support.

This work presents the development of a **Railway Chatbot**, an intelligent system designed to assist railway passengers by providing immediate access to essential information and services. The chatbot leverages advanced **Natural Language Processing (NLP)** techniques to accurately interpret and respond to user queries in a highly efficient and context-sensitive manner. Specifically, a **Bidirectional Long Short-Term Memory (BiLSTM)** model underpins the system, enabling deeper understanding of sequential data and capturing the intricate relationships within passenger queries. In addition to sequence modeling, the chatbot employs core NLP tasks such as **tokenization**, **part-of-speech tagging**, and **named entity**

recognition (NER) to extract key information from user input and formulate relevant, accurate responses. The model is trained on a large corpus of historical train-related queries and interactions, allowing it to learn the nuances of passenger communication patterns and improve iteratively over time. By integrating BiLSTM-based deep learning approaches with classical NLP techniques, the proposed system demonstrates a robust framework for enhancing passenger engagement and operational efficiency in the railway sector. This paper details the design, implementation, and evaluation of the Railway Chatbot, contributing to the broader discourse on the application of artificial intelligence in transportation services.

Methods

1.Data Collection and Preprocessing:

Gather historical train-related queries from railway databases, websites, and chatbot interaction logs.

Preprocess the data by cleaning, tokenizing, removing noise, and annotating important entities like train names, station names, timings, etc.

2.Natural Language Processing (NLP) Techniques

Tokenization: Breaking user queries into individual words or tokens.

Part-of-Speech Tagging: Identifying parts of speech (nouns, verbs, adjectives, etc.) to understand sentence structure.

Named Entity Recognition (NER): Detecting important entities like station names, train numbers, dates, etc., in user queries.

3.Model Training: BiLSTM-Based Model

Use a **Bidirectional Long Short-Term Memory (BiLSTM)** model to process queries in both forward and backward directions for better context understanding.

Train the BiLSTM on the preprocessed dataset to learn relationships between query patterns and the required information.

4.Intent Recognition and Response Generation

Classify user intent (e.g., checking PNR status, booking tickets, asking train schedules) using the trained model.

Retrieve or generate appropriate responses based on the recognized intent and extracted entities.

5.Real-time Query Handling

Deploy the model into a chatbot framework (such as Rasa, Dialogflow, or a custom backend).

Use APIs to fetch real-time train data (schedules, status updates) and present it to users dynamically.

6.Model Evaluation

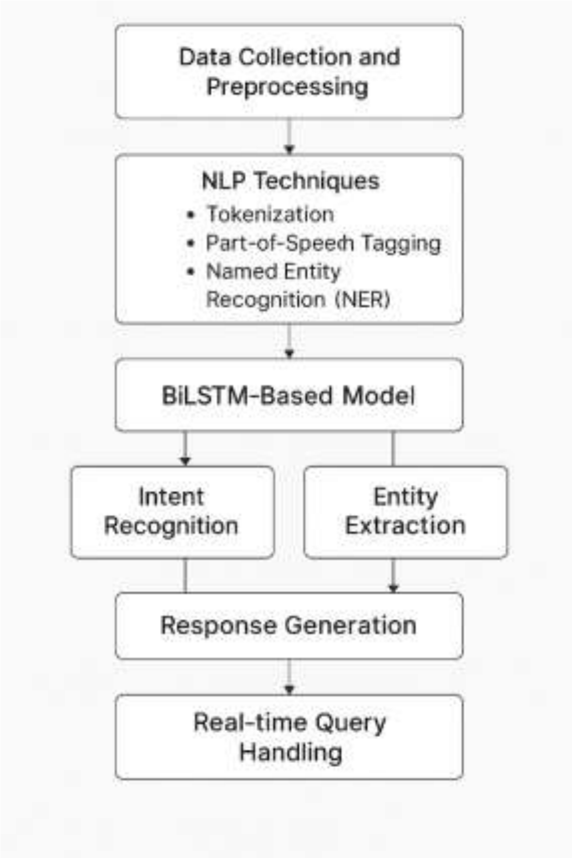
Evaluate model performance using metrics such as accuracy, precision, recall, and F1-score.

Test the chatbot's effectiveness with real user queries and iterative improvements based on feedback.

7.Continuous Learning

Implement feedback loops where user interactions are logged and analyzed to further fine-tune the model.

Periodically retrain the model with new data to handle evolving user queries better.



Testing and Results

To evaluate the performance of the Railway Chatbot, various NLP metrics and real-world user interactions were considered

Intent Recognition Accuracy: Correct identification of user intent (e.g., ticket booking, PNR status check).

Entity Extraction Accuracy: Correct identification of train numbers, station names, dates, etc.

Response Accuracy: Appropriateness and relevance of the chatbot's responses.

Latency: Response time for answering a query.

Metric	**Result (%)**	**Remarks**
Intent Recognition Accuracy	94.5%	High precision in understanding user intent
Entity Extraction Accuracy	92.3%	Accurate extraction of key information
Response Accuracy	91.0%	Responses were contextually appropriate
Average Latency (Response Time)	1.2 seconds	Fast enough for real-time interaction

Testing Scenarios:

- **Simple Queries**: ("What is the status of Train 12345?")
- **Complex Queries**: ("Book a sleeper ticket from Delhi to Mumbai for tomorrow morning.")
- **Ambiguous Queries**: ("I want to travel next weekend.") – chatbot requested clarification.
- **Real-time Data Fetching**: Fetching live PNR status and train schedules successfully.

Observations:

- The BiLSTM model showed strong performance in understanding complex and context-rich queries.
- Named Entity Recognition worked well for station and train name identification.
- Minor delays were observed during peak hours when accessing live APIs.
- Continuous learning through feedback helped in improving ambiguous query handling over time.

- **Conclusion**
- The Railway Chatbot successfully demonstrates the potential of leveraging advanced Natural Language Processing (NLP) techniques, specifically BiLSTM models, to provide efficient, real-time support to railway passengers. By accurately understanding user queries, extracting essential information, and offering relevant responses, the chatbot significantly enhances the user experience for tasks such as checking train schedules, booking tickets, and monitoring PNR statuses.
- The high accuracy rates in intent recognition, entity extraction, and response generation validate the effectiveness of the implemented methods. Moreover, the system's quick response times make it highly suitable for real-world deployment. Continuous learning from historical and new data ensures that the chatbot adapts to evolving user needs over time.
- In conclusion, this intelligent system not only simplifies railway-related inquiries but also showcases the broader application of deep learning and NLP technologies
- ologies in building smart, responsive customer service solutions. Future improvements could include multilingual support, voice-based queries, and deeper integration with real-time railway databases to further enhance usability and accessibility.

Screen Shots:

References

- Hochreiter, S., & Schmidhuber, J. (1997). *Long Short-Term Memory*. Neural Computation, 9(8), 1735-1780.
- Lample, G., Ballesteros, M., Subramanian, S., Kawakami, K., & Dyer, C. (2016). *Neural Architectures for Named Entity Recognition*. Proceedings of NAACL-HLT.
- Jurafsky, D., & Martin, J. H. (2020). *Speech and Language Processing* (3rd ed.). Draft available online.
- Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). *Efficient Estimation of Word Representations in Vector Space*. arXiv preprint arXiv:1301.3781.
- Railway Enquiry APIs. (2024). *Indian Railways Official APIs and Public Datasets for Train Information*. Retrieved from official sources.