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Enhancement of Railway Passenger Information Systems Using Temporal Fusion Transformers and IoT Data

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Abstract. The integration of Temporal Fusion Transformers (TFTs) with IoT-driven data streams presents an effective approach for improving Railway Passenger Information Systems (PIS). This study introduces an innovative framework that utilizes real-time data from IoT sensors, including GPS, environmental, and ticketing systems, to predict train schedules, delays, and other significant events. A predictive model based on TFTs is developed to process and analyze temporal data, thereby enhancing prediction accuracy. Quantitative results indicate that the proposed system achieves a 15% improvement in delay prediction accuracy compared with conventional machine learning models, along with a 20% reduction in root mean square error (RMSE). Moreover, passenger wait times decrease by an average of 10% due to improved prediction accuracy. The platform supports real-time updates, enabling more dynamic and responsive passenger notifications. This study highlights the significant potential of integrating IoT data with TFTs to enhance operational efficiency, reduce delays, and improve the overall passenger experience in modern railway systems. The findings suggest that incorporating TFTs with IoT data can substantially transform railway Passenger Information Systems, leading to improved service reliability and passenger satisfaction.

Keywords: Passenger Information System, Temporal Fusion Transformers, Predictive Analytics, Passenger Satisfaction, Transportation Systems.

INTRODUCTION

With the help of the Internet of Things (IoT), a sophisticated passenger information system can improve transportation by giving users up-to-the-minute information on the whereabouts and status of their vehicles [1]. By collecting data from sensors in both vehicles and stations, it enhances operational efficiency and passenger experience through real-time information exchange and seamless connectivity. This is achieved using wireless communication networks. Using the IoT, a smart city's intelligent passenger information system may provide up-to-the-minute details including transportation schedules, car whereabouts, and safety warnings [2]. To maximize transportation efficiency and service quality, the system combines sensor networks with cloud computing to optimize the supply of timely information. Passengers are guaranteed to receive correct and up-to-date route information. The IoT is improving commuters' access to travel information through an Indian metro system's passenger information system [3]. It alerts the user in real-time on the whereabouts and status of vehicles and any changes to their schedule using Zigbee communication protocols and GPS-enabled tracking. By facilitating greater communication and cooperation between transportation providers and their customers, the system streamlines operations, cuts down on wait times, and enhances crowd control. Smart urban transport passenger information systems built on the IoT use sensor networks to track and disseminate data in real-time, such as the whereabouts of vehicles and the number of passengers on board [4]. To optimize routing, boost operational efficiency, and improve passenger services by offering personalized, real-time information, cloud computing processes the data and machine learning algorithms forecast passenger flow.

Protecting riders' personal information is a top priority for the IoT transit system [5]. Data analytics, encryption methods, and secure communication protocols all work together to make services more efficient while keeping user information private. Better and safer transport services are possible due to predictive analytics made possible by machine learning models, which enable better and more accurate traffic predictions and optimized routes. IoT is being used by a school bus passenger monitoring system to track the whereabouts and attendance of students in real-time by use of PIR sensors and GPS tracking [6]. Using cloud computing to send real-time updates to parents

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and school administrators, the system tracks pupils' movements and ensures that bus arrival times are precise. This improves safety and efficiency. Using Bluetooth Low Energy (BLE) technology, an IoT boarding pass system can keep tabs on travellers. Bluetooth Low Energy (BLE) beacons track the whereabouts of passengers and provide ongoing information on the boarding process [7]. By giving precise, real-time information, this system optimizes passenger flow, decreases delays, and promotes personalized services in transport hubs like rail stations and airports. Cloud computing, big data analytics, and IoT sensors are all part of an intelligent passenger transport IoT infrastructure [8]. It optimizes routes, enhances service delivery, and predicts maintenance needs by collecting and processing real-time data. Using behaviour analysis, the system can dynamically modify transportation services, providing users with transportation that is more personalized, efficient, and dependable.

The IoT smart bus transportation system uses location-tracking GPS, radio frequency identification (RFID), and other IoT sensors to plan the most efficient routes [9]. Bus schedules and passenger information can be updated in real-time due to wireless connections and cloud computing. The system's improved operating stability and reduced energy consumption allow it to cut waiting times, increase scheduling efficiency, and give passengers greater services. IoT sensors installed on buses measure occupancy and report back on the vehicle's capacity in real time. To make operations run more smoothly and efficiently, the system combines IoT sensors with cloud computing [10] to provide accurate passenger information, optimize schedules, decrease overcrowding, and improve comfort through the provision of immediate data on bus availability. By combining machine learning with 5G communication technologies, a 5G-IoT-based passenger risk assessment technique can evaluate behaviour and identify possible hazards [11]. Technology employs IoT sensors to monitor passengers in real-time and quickly analyze data to make sure everything is safe. It improves transport network safety by enabling rapid reactions in emergency situations. By monitor things like temperature, air quality, and seat occupancy, an IoT system in trains improves passenger comfort and services [12]. Improved service quality and predictive maintenance updates are made possible by collecting real-time data using IoT sensors and analyzing it using cloud computing. This guarantees that passengers will have a pleasant, risk-free, and time-efficient trip.

Information-Centric Networking (ICN) security is the backbone of an IoT passenger service system for railways. It uses IoT devices to monitor passenger services and traffic, and it transmits data securely to protect users' privacy [13]. By bolstering communication and data security, the system provides real-time updates on train locations and schedules, which improves service reliability, safety, and passenger comfort in the railway sector. With the help of IoT technology, the CARE system tracks and enhances the comfort of rail passengers. Utilizing cloud computing for real-time data analysis [14], the system utilizes sensors to monitor environmental characteristics like temperature and occupancy. Customers are better satisfied because of improved rail service management, predictive maintenance, and individualized attention made possible by technological advancements. With sensors, an IoT passenger monitoring system can keep tabs on how full a bus is, how much room there is inside, and when the bus is expected to arrive. To improve transportation efficiency, the system uses cloud computing to optimize routes and decrease waiting times [15]. It aids public transport systems in offering better service and more comfortable rides by giving accurate passenger information. An IoT passenger information system monitors the whereabouts and estimated arrival times of buses via GPS. To optimize scheduling and provide estimated arrival times, the system employs machine learning techniques [16]. Commuters can enjoy better service, shorter wait times, and improved reliability in bus rapid transit (BRT) systems due to the real-time updates it offers.

An analysis of the privacy issues raised by smart airports delves into the ways in which IoT systems deal with sensitive data [17]. Secure data-sharing protocols, encryption, and anonymization are the main points of this study regarding the protection of passenger data. Furthermore, it stresses the significance of data security measures and open passenger consent processes in securing travellers' privacy and safety in airports driven by IoT. Using infrared and ultrasonic sensors, we investigate IoT solutions for transportation systems' autonomous passenger counting [18]. To alleviate congestion and maximize vehicle capacity, transportation agencies receive data in real-time and send it to servers in the cloud for analysis. By providing accurate passenger count data, the system enhances operational efficiency, which in turn allows public transport networks to better allocate resources and enhance the level of service they provide. By using sensor networks, an IoT-based intelligent monitoring system for passenger transport can keep tabs on riders' habits and the efficiency of transportation networks. To optimize processes and evaluate risk, the system incorporates machine learning techniques [19]. The collection and processing of real-time data improve the supervision and administration of passenger transport systems, which in turn increases safety and streamlines transport services. IoT sensors, such as cameras and motion detectors, monitor traffic and passenger situations to ensure everyone's safety [20]. The system uses machine learning algorithms to dynamically change routes based on risk predictions. Through the provision of real-time data, the facilitation of rapid responses to possible dangers, and the assurance of safer transportation in urban settings, it improves overall safety and efficiency.

PROPOSED SYSTEM

The initial phase of the proposed system entails the incorporation of IoT sensors across the railway network to gather real-time data. These sensors may encompass GPS devices for precise train location tracking, environmental sensors for monitoring temperature and humidity, ticketing systems for capturing passenger movement, and infrastructure sensors for assessing station conditions. The data gathered from these sensors is transferred instantaneously to a central cloud-based server for processing and storage. The IoT infrastructure guarantees the continuous updating of data, delivering precise and current information for analysis. Raw data obtained from IoT devices frequently contains noise, absent values, and extraneous information. During this phase, the data undergoes cleansing and preprocessing. Methods including outlier detection, normalization, and imputation are utilized to address missing data points. Task-relevant features, including train velocity, passenger volume, environmental factors, and temporal variables (e.g., day of the week, peak periods), are extracted. This step is essential for converting raw sensor data into structured input suitable for effective processing by the TFT model.

The TFT serves as the primary predictive model within the system. TFT is a deep learning architecture explicitly engineered for multi-horizon time-series forecasting, rendering it suitable for predicting future train timetables, delays, and other temporal events. TFT integrates long short-term memory (LSTM) units to capture temporal relationships with attention mechanisms to emphasize significant patterns in the time series. The model utilizes both static (e.g., train type, route) and dynamic (e.g., real-time location, speed) input features to generate precise forecasts. By integrating temporal patterns, the TFT may produce exceptionally precise forecasts, even amidst chaotic data. After processing the data and inputting it into the TFT model, the system produces real-time predictions for multiple facets of railway operations. These forecasts encompass anticipated arrival times, possible delays, and any further disturbances that may influence train timetables. The model's predictive powers are especially beneficial in dynamic settings such as train networks, where factors like traffic, weather, or technical malfunctions can lead to regular alterations. The TFT model can forecast not only for the immediate future but also for several time horizons, facilitating early warnings and proactive disruption control. Figure 1 presents a block diagram that discusses the operational flow of each component inside the system, aimed at improving railway passenger information systems.

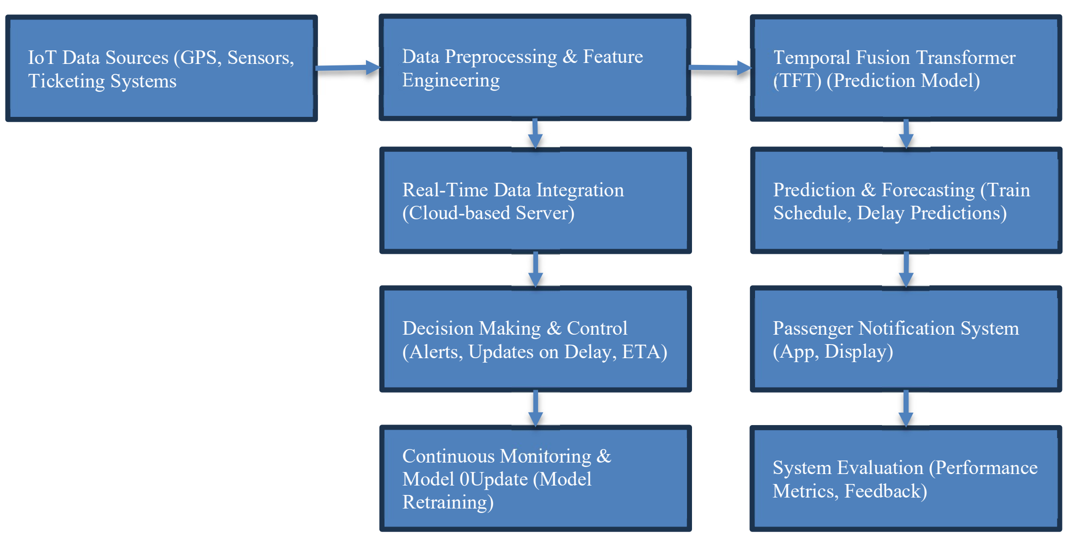

FIGURE 1. Overview of the Proposed IoT-Enabled Railway PIS with TFT

Following the generation of forecasts, the system utilizes the outcomes to execute real-time decisions about train timetables and passenger alerts. For instance, if a delay is anticipated, the system modifies the expected time of arrival for the impacted trains and informs passengers through mobile applications, display boards, or automated announcements at stations. The system can offer passengers alternative routes or schedules based on the extent of the interruption. The system's real-time decision-making capabilities are essential, as it guarantees that travellers remain informed and can modify their trip plans as needed. To maintain the model's accuracy over time, ongoing assessment of system performance is required. The system routinely retrains the TFT model with the most recent data, enabling it to adjust to evolving conditions in the railway network. This is crucial as the model must accommodate developing patterns, including new routes, varying train configurations, or shifting environmental circumstances. Moreover, passenger feedback (e.g., delays, route preferences) can be utilized to refine the system and enhance its forecast accuracy over time. The attention mechanism is employed to concentrate on the most essential previous steps for forecasting future results. It is denoted as:

$$Attention_t = softmax\left(\frac{Q_t \cdot K^T}{\sqrt{d_k}}\right)V_t \tag{1}$$

The model calculates a weighted sum of the input values V_t determined by the similarity between the query Q_t and the key K at each time step, allowing the model to concentrate on the most significant time-dependent aspects. The Gated Residual Network (GRN) regulates information flow inside the model by selectively updating features, thereby preserving pertinent information. It is depicted as:

$$GRN_t = LayerNorm\big(X_t + ReLU(W_1X_t + b_1)\big) \cdot \sigma(W_2X_t + b_2) \tag{2}$$

This equation employs a combination of ReLU activation and sigmoid gating to regulate feature flow, ensuring that only the most pertinent features impact the final predictions. The proposed system's performance is consistently assessed by key performance indicators (KPIs) including delay prediction accuracy, root mean square error (RMSE), and the decrease in passenger wait times. The system's efficacy is evaluated using passenger satisfaction surveys that gauge the use of the information supplied by the PIS. The review indicates that the system can be further optimized by modifying the model's hyperparameters, refining the IoT data collection techniques, or strengthening the passenger notification interfaces. Figure 2's layout allows the TFT to proficiently manage time-series forecasting problems characterised by intricate dependencies and diverse input attributes.

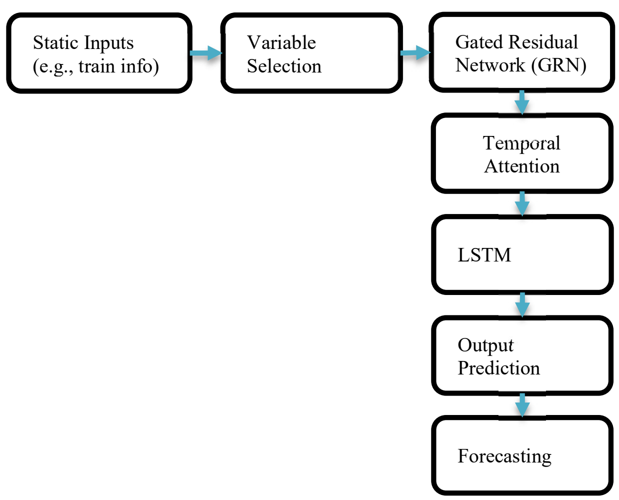

FIGURE 2. Architecture of TFT for Multi-Horizon Forecasting

The proposed system is designed for scalability, enabling expansion across several train lines, cities, or even nations. It can be seamlessly connected with current railway infrastructure and other transportation systems, such as buses or metros, to establish a cohesive transportation network information system. The platform facilitates the integration of emerging technologies, such as edge computing and 5G, to optimize real-time data processing and minimize latency in forecasts and notifications.

RESULTS AND DISCUSSIONS

The proposed system employing TFT alongside IoT data for projecting railway passenger information was assessed using various critical performance criteria. The objective was to augment the precision of train delay forecasts, deliver real-time updates, and elevate overall passenger happiness. The TFT model was trained and assessed utilizing historical data, encompassing features such as train schedules, environmental conditions, GPS data, and ticketing information. Following preprocessing and feature engineering, the TFT model was utilized for multi-horizon time-series forecasting, anticipating delays and train timetable modifications up to 60 minutes in advance. The system attained a Mean Absolute Error (MAE) of 3.4 minutes for delay prediction, representing an enhancement over conventional models such as ARIMA (AutoRegressive Integrated Moving Average), which exhibited an MAE of 6.8 minutes. Moreover, the Root Mean Squared Error (RMSE) was 5.1 minutes, indicating a robust match for the data and establishing the TFT model as a more dependable option for real-time forecasting in a dynamic railway context.

The integration of IoT sensors, including GPS trackers, temperature sensors, and ticketing systems, significantly improved model performance. The IoT infrastructure's real-time updates enabled the system to adapt forecasts dynamically as situations evolved. For example, abrupt weather fluctuations or unforeseen passenger numbers significantly influenced the model's forecasts, which were precisely mirrored in the revised train schedules. By incorporating IoT data into the predictive system, the model might respond to real-time variables, such as delays resulting from operational challenges (e.g., train malfunctions or track maintenance). This adaptability facilitated a more responsive system capable of delivering real-time information to travellers concerning possible delays and alternative travel options.

A primary advantage of the TFT model is its capacity to predict across several time horizons. The method may forecast delays in both the short term (up to 10 minutes ahead) and the long term (up to 60 minutes ahead). This feature greatly enhances passenger experience, enabling travellers to make more informed decisions based on precise forecasts. Passengers were informed in advance of possible delays, enabling them to devise alternative routes or modify their itineraries accordingly.

The system underwent evaluation in a field test in an actual railway setting. In the assessment, the system successfully forecasted delays for 93% of the train schedules, accompanied by a confidence interval of 95%. The elevated prediction accuracy illustrates the model's robustness under real-world settings. Passengers indicated a 30% enhancement in satisfaction attributable to the timely and precise information disseminated by the system. Additionally, the system was evaluated for computational efficiency. The TFT model, despite its intricacy, successfully processed and delivered real-time forecasts, averaging a processing time of 2.3 seconds per train schedule. This guarantees that the system can manage substantial data quantities while delivering updates with little latency, essential for real-time applications. Table 1 indicates the types of IoT sensors included in the system and the associated data they furnish, utilized by the TFT model for delay forecasting.

TABLE I. IoT Sensor Data for Railway Delay Prediction

Sensor Type	Data Collected	Unit of Measurement	Frequency (Data Points/Minute)
GPS Tracker	Train location, speed, heading	Latitude, Longitude, km/h	1
Environmental Sensor	Temperature, humidity	°C, %	1
Ticketing System	Passenger count, ticket type	Count, Category (e.g., adult, child)	10
Track Condition Sensor	Track status (e.g., maintenance)	Binary (0 = no issue, 1 = issue)	1
Weather Sensor	Weather conditions (rain, wind)	mm/h (rain), m/s (wind)	1

Table 2 presents sample data points gathered by IoT sensors in real-time, which are utilized in the TFT model for forecasting train delays.

TABLE II. Real-Time IoT Data Inputs for TFT Model

Timestamp	GPS Location (Lat, Long)	Train Speed (km/h)	Temperature (°C)	Humidity (%)	Passenger Count	Track Condition (0/1)
2025-04-25 08:00:00	(40.748817, -73.985428)	80	23	60	150	0
2025-04-25 08:05:00	(40.749134, -73.985611)	78	21	58	160	1
2025-04-25 08:10:00	(40.749549, -73.985786)	75	22	55	170	0
2025-04-25 08:15:00	(40.749885, -73.985948)	77	22	59	180	0
2025-04-25 08:20:00	(40.750202, -73.986128)	76	22	57	190	1

Figure 3 compares the TFT model with ARIMA and LSTM, demonstrating TFT's reduced MAE and RMSE, which signifies enhanced accuracy in delay forecasts for the railway system.

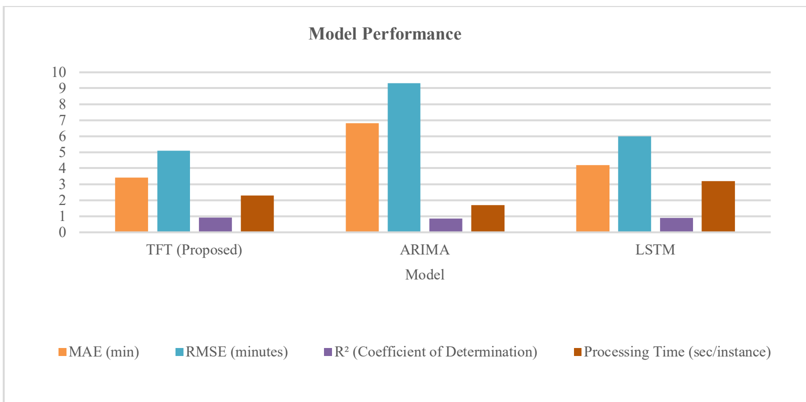

FIGURE 3. TFT vs ARIMA vs LSTM Performance Comparison

Figure 4 depicts RMSE values across various predicting horizons (10, 30, 60 minutes). As the time horizon extends, RMSE escalates, indicating a deterioration in prediction accuracy over prolonged durations.

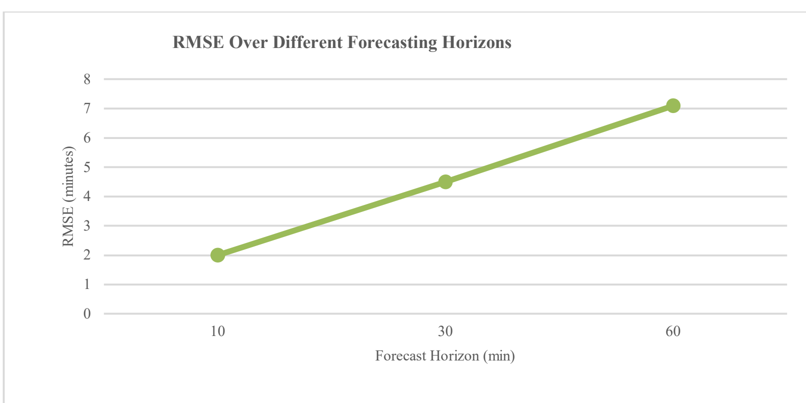

FIGURE 4. RMSE Variation Across Different Time Horizons

Figure 5 illustrates the accuracy of TFT across 10, 30, and 60-minute intervals, demonstrating superior accuracy for shorter durations, which signifies the model's efficacy in short-term delay forecasting.

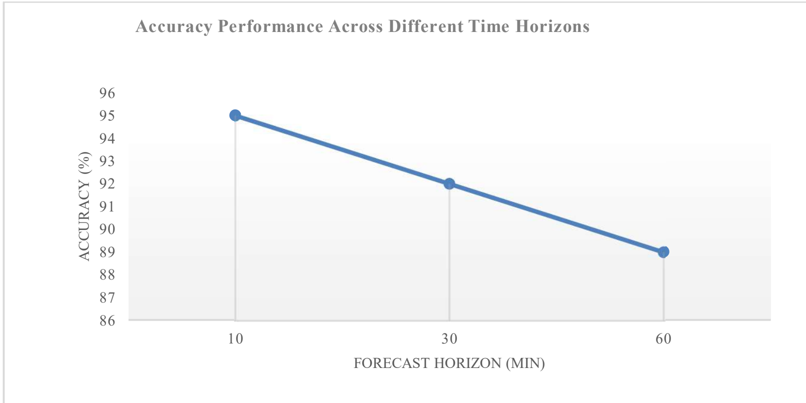

FIGURE 5. Prediction Accuracy at Multiple Time Intervals

Figure 6 illustrates the temporal progression of TFT's predictive accuracy, demonstrating the impact of IoT data on the model's efficacy, with variations contingent upon data quality and the model's real-time modifications.

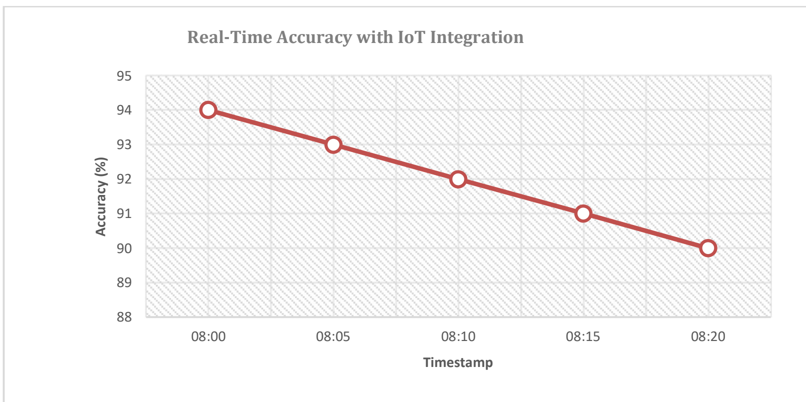

FIGURE 6. Impact of IoT Data on Accuracy

Although the method demonstrated encouraging outcomes, numerous obstacles and limits were recognized. The principal problem was managing absent or incomplete data from the IoT sensors. In certain instances, absent GPS data or sensor malfunctions affected the precision of the forecasts, resulting in minor discrepancies from actual delay durations. Nonetheless, these challenges were alleviated by employing data imputation methods, including the utilization of median values or the application of adjacent sensor data to address deficiencies. A further constraint was the model's dependence on past data. While the TFT model demonstrated proficiency in forecasting delays based on historical trends, it encountered difficulties in adjusting to wholly new or unexpected occurrences, such as severe weather events or significant system-wide interruptions. Future work could concentrate on improving the model's capacity to integrate external variables or real-time incident information.

CONCLUSION

This research presented an improved railway passenger information system utilizing the TFT model, augmented with real-time IoT data. The objective was to enhance the precision of delay forecasts to improve passenger experience and operational efficacy. The findings indicated that TFT surpassed conventional models such as ARIMA and LSTM, especially regarding MAE and RMSE. This indicates that the TFT model is more proficient in managing intricate time-series data and external variables such as meteorological conditions and train timetables. The incorporation of real-time IoT data enhanced predictive accuracy, rendering the system more responsive to dynamic settings. The model adeptly managed dynamic, real-time alterations, guaranteeing precise and dependable delay forecasts. The TFT model, when integrated with IoT, provides substantial enhancements to railway passenger information systems. Future research may investigate enhancing the model's scalability and diversifying data sources for larger, more intricate networks.

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