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# Passenger Demand Forecasting in Railways using Machine Learning

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## Abstract

*This review examines recent advancements in machine learning (ML) and deep learning (DL) techniques for demand forecasting across diverse domains, including railway passenger flow prediction, business intelligence, and student academic performance. The study compares and contrasts various methodologies, such as hybrid deep learning approaches, graph-based learning frameworks, and multiclass prediction models, highlighting their strengths and limitations. Key innovations include the integration of spatial-temporal features, handling of imbalanced datasets, and incorporation of capacity constraints. The comparative analysis reveals that while ML and DL models achieve high accuracy in specific domains, challenges remain in terms of data quality, model generalization, scalability, and interpretability. The review also identifies future research directions, such as the creation of benchmark datasets, development of hybrid and interpretable models, domain adaptation and transfer learning, real-time and scalable implementation, uncertainty and robustness modeling, and ethical considerations. Overall, this study provides valuable insights into the current state and future potential of ML and DL techniques for demand forecasting, emphasizing the need for cross-domain collaboration and the development of more reliable, transparent, and widely applicable solutions.*

***Keywords:*** *Machine Learning, Passenger Demand Forecasting, Deep Learning, LSTM, CNN, Hybrid Approaches, Intelligent Transport Systems, Urban Railway Systems.*

## 1. Introduction

Forecasting demand has become a crucial element of planning in many data-driven sectors, and the railway industry is no exception. Reliable passenger demand prediction enables transport authorities to design timetables more effectively, allocate capacity efficiently, and reduce operational bottlenecks. Traditional statistical forecasting methods, however, often struggle when faced with the irregular, nonlinear, and highly dynamic nature of real passenger-flow patterns. This limitation has encouraged researchers to explore machine learning (ML) and deep learning (DL) techniques, which have shown considerable promise in capturing complex spatial–temporal relationships. For instance, hybrid deep learning architectures have been used to model real-time metro passenger flow with greater precision [1], and advanced neural networks have proven effective for short-term demand prediction in dense urban rail systems [2]. The usefulness of ML-based forecasting extends well beyond the transportation sector. In business environments, ML-enabled analytical frameworks have supported more accurate demand estimation and strategic decision-making [3]. Similarly, educational institutions have applied multiclass prediction models to anticipate student performance, demonstrating ML’s versatility across domains involving diverse data types and decision contexts [4]. These examples illustrate that different sectors share common forecasting challenges—such as inconsistent data quality, variable patterns, and temporal dependency—and that ML techniques can address such issues more effectively than traditional approaches. Within railway applications specifically, several recent studies have introduced innovative modelling directions. Graph-based learning approaches, for example, incorporate nested travel choices and structural characteristics of railway networks, leading to more context-aware demand estimation [5]. The growing integration of digital twin technologies with DL models is also transforming real-time passenger monitoring and prediction by leveraging continuous mobile and

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sensor data streams [6]. Other works have combined wavelet analysis with kernel-based learning to strengthen short-term prediction performance [7], while multi-stage hybrid models—such as those merging LSTM with gradient boosting techniques—have demonstrated their ability to handle complex passenger-flow variations in large transit hubs [8]. Similar methodological advances have also been reported in non-transport areas such as food supply chain forecasting, highlighting the adaptability of ML for time-series modelling across fields [9]. Earlier research has consistently emphasized the need for richer feature sets and more robust modelling strategies for railway demand forecasting. For instance, studies have pointed out the importance of integrating behavioural, operational, and contextual indicators to enhance predictive reliability [10], while others have presented empirical analyses of metro and railway passenger patterns using real-world data [11]. Digital-twin-enabled forecasting continues to attract attention as an emerging solution for real-time transport management [12]. Additionally, environmental factors such as weather and climate conditions have been incorporated into DL models to better explain metro and bus passenger variations [13]. Long-distance railway demand has also been modelled using recurrent neural networks capable of learning long-term temporal dependencies [14]. Overall, although ML and DL techniques have pushed forecasting accuracy to new levels, several challenges persist—including limited interpretability, scalability concerns, and difficulties in model transferability across networks or cities. These gaps indicate the need for ongoing research on hybrid approaches, explainable models, and more generalizable forecasting frameworks suitable for real-world deployment.

## 2. Literature Review

### 2.1. A Hybrid Deep Learning Approach for Real-Time Estimation of Passenger Traffic Flow in Urban Railway Systems

Advances in intelligent transportation systems have enabled metro and railway networks to collect detailed passenger-flow information through modern sensing and monitoring tools. This continuous stream of data has created a strong foundation for developing computational models capable of forecasting passenger demand more accurately and efficiently [1]. Research in this domain generally follows two major directions: single-model approaches and hybrid deep learning approaches. Single-model techniques traditionally relied on statistical time-series strategies. Methods such as ARIMA and B-spline modelling were widely used to capture historical demand patterns and generate short-term predictions [2], [3], [4]. Although these models work reasonably well for stable and linear patterns, they often fall short when dealing with the nonlinear, fluctuating, and highly dynamic characteristics of urban passenger movement. As data availability increased, researchers began adopting machine learning and deep learning models to better capture nonlinear relationships. Algorithms such as Artificial Neural Networks, Deep Belief Networks, and LSTM architectures have shown considerable improvements in forecasting tasks by learning complex dependencies within passenger flow data [5], [6], [7]. These models demonstrated stronger adaptability compared to classical approaches and inspired further exploration into more sophisticated learning frameworks. To push predictive accuracy even further, scholars introduced hybrid models that combine statistical and machine learning techniques. Examples include Kalman filter–neural network combinations for mid-scale transportation networks [8] and hybrid neural network–ARIMA frameworks for forecasting ridership trends [9]. Ensemble approaches have also been proposed, integrating moving averages, exponential smoothing, ARIMA, and neural networks to improve model robustness and stability [10]. In addition, specialized dual-network architectures have been developed to address the complexities of railway passenger behaviour [11]. Despite their advancement, many of these hybrid systems still overlooked the combined influence of spatial structure within the rail network and temporal variations across different time intervals. More recent work has emphasized spatiotemporal modelling, acknowledging that accurate passenger flow prediction requires understanding how stations interact with one another as well as how demand evolves over time. Graph-based deep learning techniques—including Graph Convolutional Networks integrated with LSTM layers—have demonstrated strong performance in traffic flow prediction by jointly capturing spatial connectivity and temporal patterns [12], [13]. Similar concepts have been effectively applied in other transportation and engineering applications, further reinforcing the importance of spatiotemporal integration for reliable forecasting [14]. Building on these developments, the proposed hybrid GCN–LSTM framework aims to enhance real-time passenger flow estimation by extracting both spatial and temporal features from railway traffic data. This approach aligns with recent advancements in deep learning-based forecasting and offers a promising direction for improving the precision and responsiveness of modern passenger demand prediction systems [1], [15].

### 2.2. Short-Term Passenger Flow Forecasting Using ResNet–GCN–Attention LSTM

Short-term passenger flow forecasting (STPFF) plays an essential role in the efficient operation of urban rail transit (URT) networks. Accurate short-range predictions help transport authorities adjust train frequencies, manage crowding, and support passengers in planning their trips more effectively. Earlier attempts to address STPFF problems predominantly relied on traditional statistical approaches such as historical averaging, ordinary least squares regression, ARIMA, Kalman filtering, and k-nearest neighbour models [1]. While these classical methods perform reasonably well in stable situations, they often fall short when rapid changes or nonlinear travel patterns must be captured, making them inadequate for real-time operational demands. To overcome these limitations, recent studies have shifted toward deep learning–based solutions. A notable contribution in this direction is the ResLSTM model proposed in the reviewed work, which integrates three complementary neural components—Residual Networks (ResNet), Graph Convolutional Networks (GCN), and an attention-enhanced Long Short-Term Memory (LSTM) network—into a unified forecasting framework [2]. Each component addresses a different dimension of the STPFF challenge. ResNet is responsible for extracting complex spatial relationships among metro stations, while GCN encodes the underlying rail-network topology, enabling the model to incorporate structural connectivity information that traditional methods often ignore. The attention-based LSTM layer focuses on identifying the most influential temporal patterns, improving the system's ability to capture fluctuating demand over time. A unique aspect of this model is its consideration of external environmental factors—such as weather and air quality—which are rarely included in conventional passenger flow studies [3],[6],[13]. The framework processes information through four distinct input streams: inflow, outflow, spatial topology, and environmental indicators. This multi-branch strategy allows the model to produce more context-aware forecasts. The authors evaluated the system using operational data from the Beijing subway network across varying temporal resolutions (10, 15, and 30 minutes). Experimental results demonstrated that ResLSTM consistently outperformed several leading benchmark models in forecasting accuracy and stability [2],[7],[8]. Interestingly, the findings also revealed that prediction errors decreased as the interval length increased, with the 30-minute forecasts showing higher accuracy than those at 10-minute intervals. Overall, this study highlights the importance of integrating spatial, temporal, and environmental dimensions when modelling short-term passenger movements. By combining ResNet, GCN, and attention-driven LSTM components, the proposed approach represents one of the earliest efforts to incorporate air-quality-related information into URT demand prediction, offering a more comprehensive and realistic perspective on STPFF [2], [5], [12], [15].

### 2.3. Effective Demand Forecasting Model Using BI Empowered with ML

Business Intelligence (BI) has increasingly become a core component of organisational decision-making, as it supports companies in converting large amounts of raw operational data into meaningful insights. When BI is integrated with machine learning (ML), its analytical capability expands significantly, enabling more accurate forecasting of demand patterns across different time horizons. As highlighted in recent studies, BI acts as a

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comprehensive decision-support layer that collects, organises, and analyses information from multiple internal and external sources to forecast consumer needs and market behaviour [3], [9]. The demand forecasting workflow generally involves two major stages. The first is the consolidation of sales, market, and operational data through BI systems. The second stage applies ML algorithms to historical and real-time datasets, allowing predictive models to track trends, identify seasonal variations, and anticipate future demand. This combination of BI and ML mirrors forecasting trends seen in other domains, such as railway passenger flow prediction, where hybrid or deep learning models successfully utilise complex temporal data for accurate estimations [7]. The methodology integrates both quantitative analytical tools—including statistical approaches and mathematical modelling—and qualitative elements such as expert assessments and market observations. Over the years, these methods have evolved into hybrid forecasting models that blend multiple techniques to enhance performance and overcome limitations such as data noise or irregular trends [3], [9]. In the reviewed study, the proposed BI–ML framework was validated using real organisational datasets, achieving a prediction accuracy of around 92.38% [3] demonstrating its strong practical relevance. Accurate demand forecasting remains essential for strategic planning and resource optimisation, as it helps firms prepare adequate stock, streamline production activities, and respond more effectively to customer expectations. Similar approaches have shown their value in other fields, such as transportation systems, where ML-based forecasting improves the management of passenger flows and capacity planning [5], [6], [10]. The use of a scalable platform such as AWS SageMaker further illustrates that such forecasting models can be adapted across various industries without major architectural changes [3]. Overall, integrating BI with ML-driven forecasting techniques provides organisations with more precise, adaptable, and actionable insights. Beyond commercial applications, these methods offer promising opportunities for related sectors—including railway passenger demand forecasting—where accurate prediction plays a critical role in system optimisation and service reliability [11].

## 2.4. Multiclass Prediction Model for Student Grade Prediction Using Machine Learning

### 2.4.1. Importance of Predicting Academic Performance

Forecasting students' academic outcomes has become essential for higher education institutions, as it helps monitor learners' progress and guides strategic academic decisions. Studies have shown that performance is shaped by multiple factors—such as socioeconomic background, demographic variables, and learning behaviours—beyond exam results alone [4].

### 2.4.2. Growing Use of Predictive Analytics in Education

With the advancement of data-driven methods, predictive analytics supported by machine learning is being adopted widely in the education sector. These techniques help identify trends in student data, predict performance, detect early dropout risks, support academic alert systems, and even guide course recommendations [4].

### 2.4.3. Machine Learning for Grade Prediction

Several machine learning algorithms have been used to classify and predict student grades. Popular models include Logistic Regression and Naïve Bayes, along with Decision Trees (J48), Support Vector Machines, k-Nearest Neighbours, and ensemble methods such as Random Forests [4]. These algorithms assist in analysing how various academic and non-academic features contribute to grade outcomes.

### 2.4.4. Issue of Imbalanced Datasets

A major challenge observed in student-grade forecasting is the imbalance across different grade categories, where certain classes have significantly fewer samples. Many existing studies acknowledge this issue but fail to implement effective solutions to handle multi-class imbalance, reducing the reliability of model predictions [4].

### 2.4.5. Attempts to Improve Model Performance

To overcome the limitations of imbalanced datasets, researchers have applied oversampling approaches

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like SMOTE to enhance the representation of minority classes. Additionally, feature selection techniques have been explored to remove redundant attributes and improve the efficiency and accuracy of predictive models [4].

#### 2.4.6. Identified Research Gaps

Despite ongoing efforts, there remains a shortage of comprehensive studies on improving multi-class imbalanced classification for student grade prediction. There is a notable demand for integrated models that combine oversampling and feature selection to enhance prediction accuracy and robustness [4].

#### 2.4.7. Multilayered Railway Passenger Demand Estimation Considering Nested Choices: A Computational Graph-based Learning Framework

Recent studies emphasize that railway demand forecasting must move beyond the analysis of isolated variables such as boarding counts or OD pairs and instead adopt a multilevel perspective that captures the interconnected nature of passenger behaviour across stations, OD routes, and line or segment flows. This approach aligns with emerging research trends that highlight the importance of modelling complex passenger dynamics in modern rail systems [5], [11]. To support this multi-scale representation, observed demand data are transformed into structured loss functions and embedded within a hierarchical flow network. This formulation enables the simultaneous estimation of several interdependent demand variables, addressing limitations common in traditional single-layer modelling frameworks [5]. By accounting for the relationships among different demand components, the system can represent real traffic conditions more accurately than conventional models used in earlier forecasting studies [1], [7]. A key enhancement of this framework is the integration of a Nested Logit discrete choice model, which helps estimate behaviourally interpretable parameters such as service frequency, fare levels, and generalized travel times—factors that significantly influence passengers' route and service preferences [5], [10]. Embedding such policy-sensitive attributes within the network strengthens the model's usefulness for operational planning and strategic decision-making, complementing earlier work that incorporated behavioural modelling into transit demand estimation [14]. Another major advancement is the incorporation of explicit line capacity constraints. Unlike typical discrete choice models that assume unlimited capacity, this framework ensures that predicted flows do not exceed feasible train or line limits, avoiding unrealistic outcomes that have been reported in prior studies lacking such constraints [2], [6]. This capacity-aware structure also improves consistency across different types of observed demand data. The estimation problem is reformulated as a computational graph, enabling the use of gradient-based learning and modern machine learning solvers such as TensorFlow. This integration of classical transport modelling with machine learning optimization represents a significant methodological shift, allowing highly nonlinear models to be trained efficiently using backpropagation [5], while building upon advances in graph-based learning frameworks demonstrated in recent passenger flow prediction research [13]. The proposed methodology has been validated using real operational datasets, demonstrating that combining hierarchical demand structures with deep learning optimization techniques results in robust and scalable passenger demand estimates for complex railway networks. These findings are consistent with broader evidence that machine learning–driven frameworks can substantially enhance demand prediction accuracy across multiple transportation scenarios [8], [12], [15].

## 3. Comparative Analysis

### 3.1. Comparative Review

Khan et al. propose an enterprise-driven demand forecasting framework that integrates Business Intelligence (BI) with machine learning to produce weekly, monthly, and quarterly predictions using historical sales data [3]. Their model achieves a reported accuracy of 92% and demonstrates practical deployment potential through cloud-based platforms such as AWS SageMaker. However, despite its strong performance, the applicability of the system remains largely confined to commercial forecasting contexts, rather than broader operational domains

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such as transportation analytics or educational prediction systems. In contrast, Bujang et al. examine predictive modelling within the higher education ecosystem by evaluating six machine learning classifiers—Decision Trees, Support Vector Machines, Naïve Bayes, k-Nearest Neighbours, Logistic Regression, and Random Forest—for student grade prediction [4]. Their study makes a substantive methodological contribution through the integration of SMOTE for imbalance management, accompanied by feature selection to optimize model robustness. This combined strategy yields an exceptionally high F-measure of 99.5%, demonstrating a critical advancement in addressing multi-class imbalance in academic performance prediction. In the transportation domain, recent work has explored railway passenger flow forecasting under atypical or irregular operating conditions using deep learning and statistical modelling approaches [7], [8]. These studies successfully capture abnormal demand variations such as disruption-induced spikes or drops in ridership. Nonetheless, they are limited in their treatment of multi-layered demand dynamics, including origin–destination interactions, station-level flow composition, and aggregate network congestion behaviour. A more comprehensive modelling strategy is introduced by Wang et al., who develop a multilayered railway passenger demand estimation framework that integrates Nested Logit-based behavioural modelling with computational graph learning [5]. This approach simultaneously estimates origin–destination distributions, boarding and alighting volumes, and segment-level passenger flows. By incorporating capacity constraints, the model avoids unrealistic congestion scenarios and enhances behavioural interpretability. Furthermore, its implementation in TensorFlow enables efficient optimization through backpropagation, demonstrating an effective fusion of traditional transport modelling with modern machine learning. Additional contributions to educational analytics further highlight the importance of imbalance-aware modelling. A related multiclass student grade prediction study strengthens this perspective by demonstrating that achieving perfect class balance is not inherently necessary; rather, optimal tuning of SMOTE parameters and targeted feature selection substantially improves predictive stability [4]. This reinforces the broader methodological insight that careful pre-processing can significantly enhance classifier performance across domains.

### 3.2. Comparative Insights

#### 3.2.1. Domain of Application

The reviewed studies collectively illustrate the broad applicability of predictive analytics across commercial, educational, and transportation environments. BI-driven enterprise forecasting is represented by [3], higher education student performance prediction by [4], and multi-scale transportation demand modelling by [8], [13]. This diversity highlights the adaptability of machine learning techniques to domain-specific data structures, constraints, and operational objectives.

#### 3.2.2. Techniques and Methodologies

Studies such as [3], [7], leverage hybrid statistical–machine learning approaches, whereas [4] emphasizes the critical role of imbalance-handling techniques (e.g., SMOTE, feature selection). The multilayered framework in [5] advances methodological innovation by integrating discrete choice modelling with computational graph-based optimization, demonstrating the potential of combining behavioural theory with deep learning architectures.

#### 3.2.3. Innovative Contributions

Each work presents unique advancements: [3] integrates BI tools with ML for enterprise demand forecasting; [4] establishes a highly effective strategy for managing multi-class imbalance; [7] propose frameworks for modelling disruption-sensitive passenger flows; and [5] achieves a unified representation of multi-level railway demand while embedding capacity constraints. These innovations collectively expand the methodological landscape of predictive modelling across sectors.

#### 3.2.4. Accuracy and Validation

Performance outcomes vary with the domain and modelling objectives. The BI–ML framework in [3] reports a prediction accuracy of 92%. The imbalance-focused educational models in [4] achieve superior performance with an F-measure of 99.5%. The passenger flow models in [8], and [13] demonstrate

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robust handling of anomaly conditions in transport networks, while the computational graph–based approach in [5] validates its capacity to estimate complex, multi-layer demand structures using TensorFlow-enabled optimization.

# 4. Challenges and Future Directions

## 4.1. Challenges

### 4.1.1. Data Availability and Quality

Many studies rely on real-world datasets—including those used in sales prediction, student grade modelling, and passenger flow forecasting—but these datasets often contain noise, missing values, or severe class imbalance [3],[7]. The lack of standardized benchmark datasets across domains further restricts the ability to compare machine learning models fairly and consistently.

### 4.1.2. Model Generalization

Although several domain-specific models demonstrate strong predictive capacity—such as deep learning frameworks applied to railway passenger flow [1],[5],[6] or classification models used in educational analytics [4] their transferability across domains remains uncertain. This issue is especially prominent when models are trained on small or imbalanced datasets, increasing the risk of overfitting [4].

### 4.1.3. Scalability Constraints

Complex architectures used in transportation research, including hybrid GCN–LSTM or Nested Logit combined with machine learning [5], [8], require considerable computational power and may face challenges in real-time deployment. Meanwhile, models developed for business and educational applications [3], [4] have yet to be validated in large-scale, heterogeneous environments, limiting their scalability.

### 4.1.4. Interpretability of Machine Learning Models

Deep learning models—such as LSTM-, CNN, and GCN-based frameworks offer high accuracy in predicting railway passenger flows [1], [2], [6], but they often function as “black boxes.” Stakeholders like transport planners, educators, and business managers require clear interpretability to support informed decision-making. Current models rarely offer transparent explanations.

### 4.1.5. Managing Uncertainty and Anomalies

Although some transport-focused studies consider disruptions or abnormal travel patterns [8], many predictive models still overlook uncertainty aspects, such as sudden fluctuations in sales, irregular food demand [9], or abrupt changes in academic performance. Probabilistic modelling and robust prediction methods remain insufficiently explored.

## 4.2. Future Work

### 4.2.1. Development of Benchmark Datasets

Future research should prioritize building open, standardized datasets for business forecasting, educational analytics, and transport demand modelling. Such benchmarks would support reproducibility and enable systematic cross-model comparisons across studies [3], [4], [11].

### 4.2.2. Advancement of Hybrid and Interpretable Models

There is a growing need to integrate machine learning accuracy with the transparency of traditional models. This includes research on explainable AI, attention-based architectures, and hybrid frameworks that combine discrete choice models with deep learning approaches used in passenger flow forecasting [5], [10].

### 4.2.3. Domain Adaptation and Transfer Learning

Future studies should explore whether models developed in business forecasting [3] or education analytics [4] can be adapted to transportation domains [1], [2]. Domain adaptation and transfer learning techniques may help enhance generalization and reduce the need for extensive retraining.

### 4.2.4. Real-Time and Scalable Implementations

To achieve real-time forecasting—especially in dynamic environments such as rail transit—models should leverage cloud-based infrastructures, edge devices, and distributed machine learning frameworks. These advancements are essential for high-frequency flow prediction models such as LSTM-based systems [8], [14].

### 4.2.5. Uncertainty and Robustness Modelling

Future work should emphasize probabilistic forecasting, robust optimization, and uncertainty quantification. These approaches are crucial for managing disruptions in public transport [6], irregular food demand patterns [9], or performance variations in educational settings [4].

#### 4.2.6. Ethical and Fairness Considerations

As predictive analytics are increasingly used in decision-making environments especially in education and business future research must ensure fairness and minimize algorithmic bias. This includes avoiding discriminatory outcomes against minority groups, underperforming students, and small-scale enterprises, while ensuring that machine learning systems operate transparently and responsibly.

## Conclusion

This review has examined a wide range of recent works applying machine learning and deep learning across domains such as railway passenger demand estimation, business and market forecasting, and the evaluation of student academic outcomes. Collectively, these studies illustrate that modern computational models are highly effective at uncovering hidden structures in large datasets and providing accurate short-term predictions. Approaches such as ARIMA, Kalman filtering, neural networks, graph-based models, and LSTM architectures consistently outperform conventional statistical techniques, highlighting the progress achieved in data-driven prediction. Despite these advances, several recurring issues limit the broader practical adoption of these methods. Persistent challenges including imbalanced datasets, limited interpretability, computational constraints, and difficulties in real-time implementation—continue to restrict scalability and real-world applicability. Moreover, the reliance on narrowly focused, domain-specific datasets often hinders the transferability of models across different operational contexts. Overall, forecasting systems built on machine learning principles show considerable potential to strengthen decision-making in transportation, educational planning, and business analytics. Addressing the existing limitations by developing hybrid modelling approaches, improving model transparency, creating shared benchmark datasets, and designing systems capable of large-scale deployment will be essential for enabling more reliable, generalizable, and trustworthy prediction frameworks in the future.

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