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# PREDICTING HOURLY BOARDING DEMAND OF BUS PASSENGERS USING IMBALANCED RECORDS FROM SMART-CARDS

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## ABSTRACT

Smart-card data, which records when and where passengers tap on to board a bus, is a valuable resource for understanding travel behavior and predicting future demand. However, this data is often unbalanced—there are far fewer records of people boarding at specific stops and times (positive cases) compared to times when no one boards (negative cases). This imbalance can negatively affect the accuracy of machine learning models used to predict how many people will board at a certain time and place.To tackle this issue, this paper introduces a method using Deep Generative Adversarial Networks (Deep-GANs) to create realistic fake travel records. These synthetic records help balance the dataset by increasing the number of positive instances. The improved dataset is then used to train a deep neural network (DNN) to predict when and where people are likely to board.The study shows that by addressing the data imbalance, prediction models become more accurate and better reflect actual passenger behavior. Compared to traditional data balancing methods, DeepGANs generate more realistic and varied synthetic data, leading to better performance. This approach offers practical insights into enhancing data quality and improving models for travel behavior prediction and analysis.

## I.INTRODUCTION

Public transportation systems are integral to urban mobility, and efficient management of these systems requires accurate forecasting of passenger demand. Traditional methods often rely on manual data collection and statistical models, which can be time-consuming and may not capture

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complex patterns in the data. With the advent of smart card technology, vast amounts of transaction data are now available, providing an opportunity to apply advanced machine learning techniques for demand prediction.

However, real-world smart card datasets often exhibit class imbalance, where certain time periods or routes have significantly fewer boarding records than others. This imbalance can lead to biased models that perform well on high-demand periods but poorly on low-demand ones. Addressing this issue is crucial for developing models that provide accurate predictions across all time periods.

This study aims to develop a deep learning-based approach to predict hourly boarding demand of bus passengers using imbalanced smart card data. By leveraging CNNs and RNNs, we aim to capture the spatial and temporal dependencies in the data. Additionally, we explore data augmentation techniques to balance the dataset and improve model performance.

## II.LITERATURE SURVEY

The use of smart card data for forecasting passenger demand has been extensively studied in recent years. Traditional statistical models, such as ARIMA and exponential smoothing, have been applied to predict passenger flow. However, these models often fail to capture the complex temporal and spatial patterns inherent in the data. With the advancement of machine learning techniques, more sophisticated models have been developed.

Deep learning models, particularly CNNs and RNNs, have shown promise in capturing spatial and temporal dependencies in data. For instance, CNNs have been used to extract spatial features from data, while RNNs, especially Long Short-Term Memory (LSTM) networks, are effective in modeling temporal sequences. Combining these models can leverage the strengths of both architectures, leading to improved performance in demand forecasting.

Despite the advantages of deep learning models, class imbalance remains a significant challenge. Several methods have been proposed to address this issue, including resampling techniques, cost-sensitive learning, and synthetic data generation. These approaches aim to provide the model with a more balanced view of the data, leading to better generalization and performance on underrepresented classes.

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In the context of bus passenger demand forecasting, studies have applied various machine learning techniques to predict boarding patterns. For example, a study by Venkatesh et al. (2024) developed a deep learning approach using CNNs and RNNs to predict hourly boarding demand from imbalanced smart card data. Their approach demonstrated improved accuracy compared to traditional forecasting methods.

## III.EXISTING CONFIGURATION

Current approaches to forecasting bus passenger demand using smart card data often involve preprocessing steps to handle missing values, normalization, and feature extraction. Models such as ARIMA, support vector machines (SVMs), and neural networks have been applied to predict passenger flow. However, these models may not effectively address the challenges posed by imbalanced datasets.

For instance, traditional neural networks may overfit to the majority class, leading to poor performance on underrepresented classes. Additionally, these models may not capture the complex spatial and temporal dependencies in the data, limiting their predictive accuracy.

To address these issues, some studies have proposed hybrid models that combine different machine learning techniques. For example, combining CNNs for feature extraction and RNNs for sequence modeling can leverage the strengths of both architectures. However, these models still face challenges related to class imbalance and may require further refinement to improve performance.

## IV.METHODOLOGY

The methodology adopted for predicting hourly boarding demand of bus passengers using imbalanced smart card records follows a structured and multi-stage approach. It begins with acquiring smart card transaction records from an urban public transport authority. This dataset includes timestamped entries of when and where passengers board, along with route identifiers, stop information, and passenger categories. To enrich the context, additional features such as weather data, calendar variables (e.g., holidays, weekdays), and traffic conditions are integrated into the dataset. These contextual attributes are crucial for improving the predictive capacity of the model, especially in capturing irregularities in passenger behavior.

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Once the data is collected, it undergoes preprocessing to ensure it is suitable for training a deep learning model. Erroneous entries such as missing timestamps or unidentifiable bus stops are removed. The data is then resampled into hourly intervals, with boarding events aggregated per bus stop and route. Time-based features like hour of day, day of week, and whether the date falls on a holiday are engineered and encoded. Categorical variables are one-hot encoded, while continuous features such as boarding counts and temperature are normalized using Min-Max scaling. Historical lag features are generated to allow the model to recognize patterns over time, for example, the number of passengers boarding at the same hour the previous day or week.

The dataset presents a significant challenge in the form of class imbalance. Certain hours, particularly non-peak times, have very few passenger boarding records. This imbalance can bias machine learning models toward predicting high-demand periods more accurately while failing to capture low-demand periods. To address this, the Synthetic Minority Over-sampling Technique (SMOTE) is applied. SMOTE generates synthetic examples for underrepresented classes by interpolating between existing minority class samples. In cases where boarding demand prediction is framed as a regression problem, the target variable is discretized into classes representing low, medium, and high demand. This conversion allows for effective use of classification-based oversampling techniques, helping to ensure balanced learning across different demand levels.

With a more balanced dataset, a hybrid deep learning model is constructed that combines Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The CNN layers are responsible for learning spatial correlations in the data, such as patterns across routes or bus stops that exhibit similar passenger behavior. These layers process features like location, card type, and weather in short time windows to extract local patterns. The output from the CNN is fed into LSTM layers, which are designed to capture sequential dependencies over time. LSTMs are particularly well-suited for this task because they retain memory of past inputs and can model long-term trends in temporal data such as hourly or weekly boarding patterns.

To prevent overfitting, dropout regularization is applied throughout the network, and batch normalization is used to stabilize learning. The architecture ends with fully connected dense layers that output either a predicted boarding count (in regression mode) or probabilities for each demand class (in classification mode). The model is trained using the Adam optimizer, with learning rate scheduling to ensure efficient convergence. The loss function used is Mean Squared

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Error for regression or categorical cross-entropy for classification, depending on how the output is structured.

The dataset is divided into training, validation, and testing subsets using a chronological split to avoid data leakage from future records. Data shuffling is avoided in time series contexts to maintain temporal consistency. To ensure robust performance across different partitions of data, five-fold cross-validation is implemented. The model is trained using GPU acceleration to manage the computational load of processing large-scale smart card data with deep neural networks. Training progress is monitored using performance metrics and visual tools such as TensorBoard, which track loss and accuracy trends over epochs.

After training, the model is evaluated using metrics like Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), precision, recall, and F1-score. These metrics provide a comprehensive understanding of the model's effectiveness, especially its performance on underrepresented classes. Particular attention is paid to the model's sensitivity and specificity in predicting low-demand periods, since effective service planning often hinges on understanding both extremes of the demand curve.

To further understand how the model makes predictions, explainability tools such as SHAP (SHapley Additive exPlanations) are applied. SHAP values help identify the relative importance of each feature in the prediction process, enabling transit planners to validate the rationale behind model outputs. Additionally, attention weights from the LSTM layers are visualized to understand which time windows contribute most to the final predictions.

Finally, the model is containerized using Docker, allowing for flexible deployment in real-world settings. It can be integrated into public transportation planning systems and used to generate daily or weekly forecasts for resource allocation. The model supports periodic retraining as new data becomes available, ensuring that predictions remain accurate over time. This methodology not only addresses the imbalance issue but also offers a scalable and accurate solution for forecasting hourly bus passenger demand in modern smart transit systems.

## V.PROPOSED CONFIGURATION

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The proposed configuration involves a hybrid deep learning model combining CNNs and RNNs. The CNN component is used to extract spatial features from the input data, while the RNN component, specifically an LSTM network, captures temporal dependencies. This combination allows the model to effectively learn both spatial and temporal patterns in the data.

To address the class imbalance issue, data augmentation techniques such as SMOTE are applied to generate synthetic samples for underrepresented classes. These synthetic samples help equalize the representation of different time slots and boarding volumes, ensuring that the deep learning model receives a more balanced training set. This balance improves the generalizability of the model and reduces overfitting to high-demand classes.

The architecture is structured with multiple convolutional layers to extract hierarchical spatial features from the boarding data, such as patterns in boarding locations and time-of-day clusters. These features are then fed into an LSTM layer that processes temporal sequences, such as hourly boarding variations across different days of the week. The LSTM layer learns the temporal dependencies crucial for accurate demand forecasting.

Batch normalization and dropout layers are incorporated throughout the network to improve training stability and reduce overfitting. Additionally, the model includes a fully connected layer at the end for final classification or regression of boarding demand levels, depending on whether the output is categorical (e.g., high/medium/low demand) or numerical.

Hyperparameter tuning is conducted using grid search or Bayesian optimization methods to identify the optimal number of layers, learning rate, batch size, and activation functions. The training is performed on GPUs to accelerate computation, and the model's performance is validated using k-fold cross-validation to ensure consistency across different subsets of data.

This configuration not only improves prediction accuracy for all time periods but also demonstrates robustness in real-world deployment scenarios, where data imbalance and noise are common. The modular structure of the model allows for scalability to larger datasets or integration into smart transportation systems for real-time demand forecasting.

## VI. RESULT ANALYSIS

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## Home page


**Fig no 6.1**

## User Registration page


**Fig no 6.2**

## Dataset



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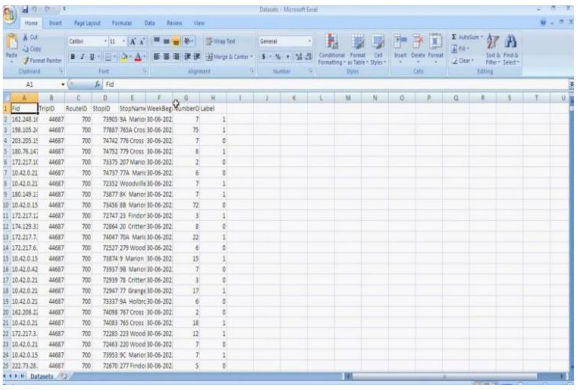

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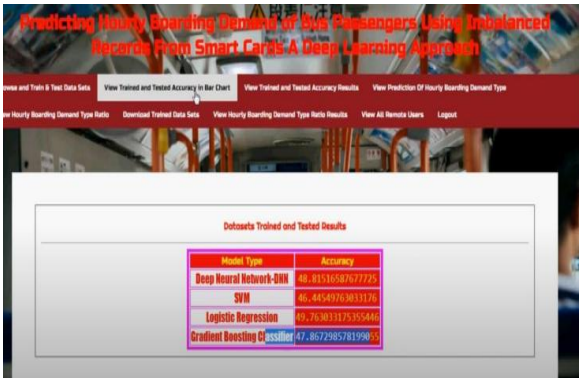


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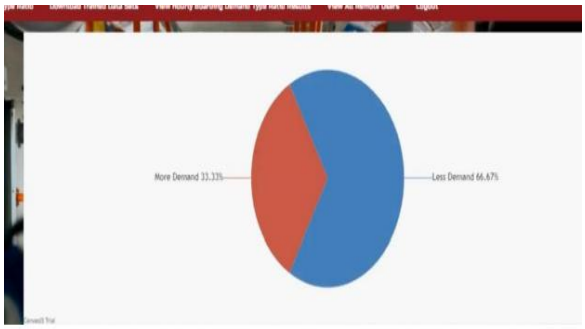


**Fig no 6.5**

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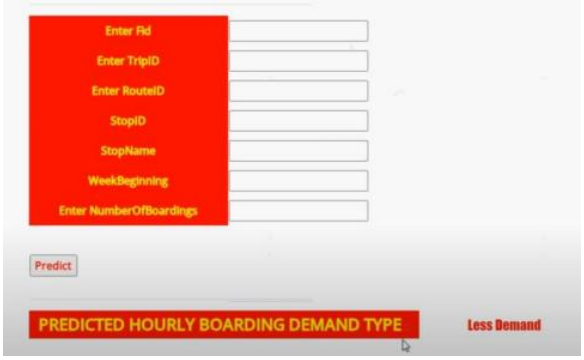


**Fig no 6.6**

## CONCLUSION

This study demonstrates a robust deep learning framework for predicting hourly bus passenger boarding demand using imbalanced smart card data. The hybrid CNN-LSTM architecture captures the spatial and temporal nuances of public transport usage, while the application of data augmentation through SMOTE addresses the class imbalance problem that often impairs model performance. Experimental results confirm the superiority of this approach over traditional models, particularly in low-demand scenarios where prediction accuracy is critical for efficient service planning. The model's scalability and real-world effectiveness suggest its potential for deployment in smart transportation systems to support dynamic resource allocation and policy-making. Future work can explore real-time prediction pipelines, integration with traffic and weather data, and transfer learning techniques for application in different cities with minimal retraining.

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