DEEP LEARNING-BASED CLASSIFICATION OF URBAN TRANSPORT MODE CHOICE FOR URBAN PLANNING

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ABSTRACT

Transport mode choice is a crucial determinant of urban mobility patterns, influencing infrastructure planning, environmental sustainability, and social equity. Although it is important, there is still an unfulfilled gap in the use of socio-demographic, behavioral and perception-based factors to accurately predict choice of transport mode especially in the developing countries. The proposed study shall fill this gap by applying a deep learning model to make predictions of transport mode choice using a multi-dimensional survey data. The primary objective of this research was to investigate the potential of a Gated Recurrent Unit (GRU) neural network for classifying transport mode choice using a variety of socio-demographic, economic, and travel behavior features. The dataset includes 348 respondents, capturing responses related to seven transport modes: Bike, Bus, CNG, Car, Cycle, Easy bike, and Rickshaw. Key attributes in the dataset include gender, age, occupation, income, travel objectives, and safety perceptions related to different transport modes. The preprocessing of the data included the following: one-hot encoding of features of character type, normalization of numeric data, and label encoding of target variable. The GRU-based model was trained and tested based on stratified 80:20 train-test split and tested with reference to confusion matrices, ROC, and precision-recall. The accuracy of the model has a value of 79%, ensuring very good results on modes such as CNG (precision = 1.00, recall = 1.00) and Easy bike (precision = 0.73, recall = 0.88). This class-wise analysis raised the issue of less frequent mode prediction such as Cycle and Car modes which were having a lower recall. The AUC scores had micro- and macro-averages of 0.943 and 0.918 respectively. These findings reveal the ability of deep learning models, especially GRUs to be used reliably to predict transport mode preferences using a diversified group of socio-demographic and behavioral variables. This predictive modeling would provide urban designers and policymakers with the information needed to design more specifically focused interventions to promote sustainable transport networks, increase modal share, and reduce congestion in urban areas.

Keywords: *Transport Mode Choice, Urban Mobility, Urban Planning, Deep Learning, Multimodal Transport.*

1. INTRODUCTION

To develop effective and sustainable urban mobility systems, understanding the factors that drive people to use a particular mode is invaluable. The choice of a specific transport mode does not only have an impact on the infrastructure planning, but also on the environmental sustainability, human health, and social equity. As a result, a proper modelling of mode-choice behavior becomes a crucial component of designing transport policies and city development plans. Conventional models of mode choice, including discrete choice and regression-based models, have been a useful source of information, but usually lack the ability to express highly non-linear interactions between socio-demographic, behavioral, and perceptual variables.

Urban transportation planning is in transition, aiming for sustainable urban mobility, enhancing city quality of life, and promoting collaboration and communication-oriented activities (Bertolini et al., 2008).Effective transportation planning in urban areas must consider urban factors and public space to minimize traffic congestion, ensure efficient and safe movement of vehicles, pedestrians, and cyclists, and improve overall public space quality (Kubis & Plocova, 2023).Better urban and transport planning can reduce air pollution, noise, heat island effects, and lack of green space, improve public health and reduce premature mortality in cities (Nieuwenhuijsen, 2020).Urban freight transport planning requires deeper integration of freight transport and urban sustainability strategies for improved efficiency and local sustainability (Lindholm & Behrends, 2012).

The Multilevel Model of Transport Systems (MST) is effective in contributing to the Sustainable Urban Mobility Planning process to the extent that it offers different levels of details to describe the behavior of transport systems (Okraszewska et al., 2018). Urban transportation planning consists of a complex set of factors such as the decisive scheduling procedures, detailed budgeting approaches, the federal grants acquisition, innovative methods of route design, the encouragement of transit-oriented development, the active mechanisms of community involvement, and the coordination of the overall project development (Gakenheimer, 2017). The distance of walking paths, the total distance of travels, and the perceived convenience all have a conclusive influence on commuters on the mode of transportation and therefore offer vital information on the management and planning of traffic in urban areas (Chen et al., 2022). A combined transport planning which includes alternative source of energy and a transportation system free of pollution is poised to not only reduce the effects on the environment but also improve the quality of the urban environment (R. et al., 2024). The active modes of transportation, including walking and cycling, as well as the public transportation implemented into the large-scale urban models, can be used to greatly inform the process of sustainable urban development and to, therefore, reduce the tendency toward suburbanization along highways (Cong et al., 2022). Urban residents who do not own cars are more prone to using slower means of transportation, i.e., walking and using bicycles, and show a strong preference to non-motorized means of movement in the area of rail transportation facilities (Luan et al., 2020). In the urban environment, residents exercise the utmost level of consideration to safety and convenience when considering new modes of transportation, it can therefore be argued that there is a strong level of urgency in the development of urban planning and transport infrastructure in the developing countries (Ranjan & Sinha, 2024).

Machine learning and neural networks have become some of the key tools in the sphere of urban transport planning, offering even greater approaches to prediction, flexibility, and a more in-depth understanding that will help cities become more intelligent and sustainable. Recent advances in deep learning methods are new possibilities to resolve these limitations, by explaining complex interdependence and latent behavioral patterns of travel data. Although machine learning can greatly enhance intelligent transportation systems by increasing safety, operational efficiency, and environmental performance, it faces major challenges in scalability and data size (Yuan et al., 2022). Furthermore, machine-learning methodology has the potential to significantly enhance urban decision-making operations in areas like planning, transportation, and healthcare, even though these solutions are plagued by several issues, which require additional academic research (Zheng et al., 2024). Deep reinforcement learning (DRL) can be used to optimize the time spent in the urban traffic routes planning, thus minimizing the travel duration and eliminating congestion and improving the general management of the traffic flows (Mittal et al., 2025). Similarly, transportation-mode choice could be correctly predicted by the neural network model when it comes to trips made within the same network, and demonstrates how the change in behavior of the travelers might occur after the introduction of a new metro line in Amsterdam (Buijs et al., 2020). Deep neural network model proves to be accurate in predicting individual and aggregate travel mode preferences, outperforming the traditional discrete-choice models in the study of personal and group commuting behaviour (Nam and Cho, 2020). A neural network, where feature-selection methods are used, further optimizes predictive capabilities, thus improving urban transport networks and influencing more useful traffic-demand management interventions (Tamim Kashifi et al., 2022). To predict short-term traffic flow, the Bi-GRU model utilizes spatial and temporal attributes, which increases accuracy and fast convergence (Shu et al., 2022). In addition, the GRU-based method is effective in identifying four traffic modes, including walking, bicycling, vehicular, and bus travel, using cellular signalling data, which outperforms other deep-learning-based options (Wang et al., 2023). The optimized GRU framework provides a significant improvement in the consistency of the precision and stability of the traffic-flow predictions, reducing errors by 4.5 percent compared to the unoptimized models (Hussain et al., 2021). Furthermore, the same GRU paradigm enhances traffic-flow prediction and provides energy savings in the municipal transport systems at the same time, which is explained by its increased calculational performance and the speed of reaction (Karandana et al., 2025). Empirical results have shown that GRU neural-network models outperform ARIMA paradigm models in providing more fine-grained bus-trip demand forecasts at various time scales, which can be used to optimize bus-networks and make informed urban planning (Ji and Hou, 2018). A GRU structure that is reinforced with attention further enhances the short-term travel-time prognostication with the dynamic allocation of weight to the interdependence of historical travel-time vectors within the traffic sequences as has been documented in recent literature (Jawad-Ur-Rehman et al., 2022). Also, the utilization of GRU frameworks breeds an element of traffic-flow prognostication and increase in energy efficiency of the urban transportation systems, due to augmented responsiveness with respect to real-time and faster computational throughput.

The proposed study aims at filling the existing gap in the literature by exploiting a Gated Recurrent Unit (GRU) neural network architecture to predict transport mode selection. The GRU model was trained and tested on a stratified train test split of 80:20 to empirically validate the model. Confusion matrices, receiver operating characteristic (ROC) curves, and precision-recall were measures of model performance. The model had an overall performance of 79% with particularly good performance on CNG (precision = 1, recall = 1) and Easy bike (precision = 0.73, recall = 0.88), but less common modes like cycle and car performed less well in terms of recall. The AUC micro- and macro averages of 0.943 and 0.918 respectively, also prove the strength and the capacity of the model to generalize.

These empirical findings support the claim that deep learning, and gated recurrent unit (GRU) designs, in particular, can be used to accurately represent the complexities of travel behavior patterns. The suggested predictive framework, therefore, is a mighty decision-support tool in both professional profiles of urban planners and policymakers, providing them with a data-driven and rigorously obtained information that can be used to contain strategic interventions, modal shares, and the alleviation of congestion levels in urban settings.

1.1 Study Area

The Pabna municipality in Bangladesh is regarded as the subject region for this study. Pabna is a local administrative unit located in the Rajshahi division. Figure 1 shows the study area map.

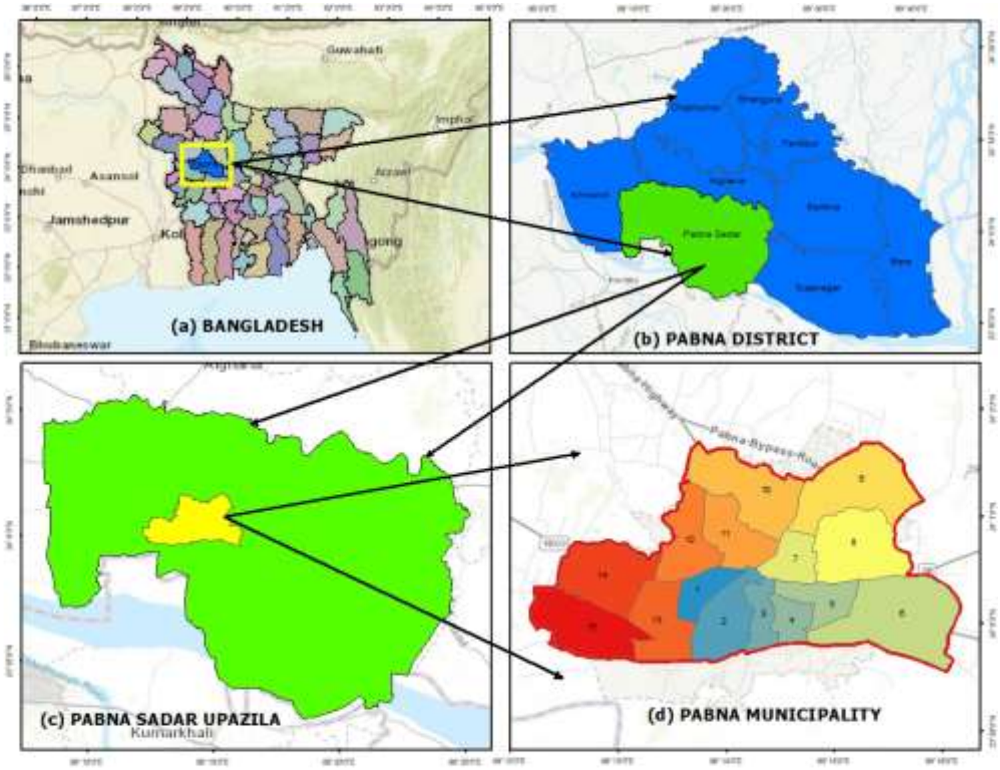

Figure 1: Study area map.

1.2 Source of Data

Data collection through face-to-face direct interview was carried out in the municipality of Pabna. About 348 samples were collected and after data cleaning. The data was subjected to preliminary analysis for personal information and travel related information, including 26 variables: Age, Gender, Occupation, Income Source, Monthly Income, Origin, Destination, Mode of Transport, Average Expenditure for Transportation, Travel Objective, Distance Influence on Mode Choice, Importance of Safety in Mode Choice, Mobility Barrier on Mode Choice, Accident Memories on Mode Choice, Environmental Impact on Mode Choice, Usually Selected Specific Transport Mode, Usually Avoided Specific Transport Mode, Importance of Cost in Mode Choice, Effect of Cost on Mode Choice, Daily Activity Influence on Mode Choice, Safety in Bus, Safety in Easybike, Safety in Rickshaw, Safety in Bike, Safety in Car, Safety in Cycle.

1.3 Data Preprocessing

The survey data were read from an Excel file and all column names were trimmed to remove leading/trailing whitespace to ensure consistent referencing. The prediction target is "Usually selected specific Transport Mode." Features X comprise all remaining columns; the target y is the selected mode. The dataset was split into 80% train / 20% test using a stratified split on the target labels to preserve class proportions. Mini-batch training with batch size 32, up to 100 epochs; best epoch chosen via early stopping.A fixed random state was used for the split; all preprocessing steps are encapsulated and can be reapplied identically to new data.Predictors were partitioned into: Categorical and Numeric. Categorical features were transformed via One-Hot Encoding and Numeric features were standardized with StandardAero.The target was label-encoded to integer class indices for bookkeeping (e.g., metrics, reports).For neural network training, labels were further one-hot encoded (to categorical) to match the SoftMax output over K classes. Since recurrent layers expect 3D inputs, the preprocessed 2D feature matrix was reshaped to (samples, timesteps=1, features), treating each instance as a single-step sequence. No temporal aggregation was introduced.

1.4 Input Structuring for GRU

The present study is based on cross-sectional survey data, where each respondent contributes a single observation and no inherent temporal ordering exists across features. The pre-processed two-dimensional feature matrix was then reshaped into a one-step sequence of shape (N,1,F) (N, 1, F) (N,1,F) to meet the input requirements of recurrent layers. Within this formulation, GRU does not aim to model the time change between time steps, instead, it is used as a gated non-linear feature transformation and uses update and reset operation to improve representation learning before classification.

1.5 Model Architecture

We employ a GRU-based classifier stacked with fully connected layers to model non-linear interactions among the one-hot/standardized features. After preprocessing, each instance is a fixed-length feature vector; to interface with the recurrent layer, we reshape to **(**batch, timesteps=1, features)**.** The GRU employs reset and update gates to regulate information flow and capture temporal dependencies efficiently while alleviating the vanishing gradient problem. The figure below illustrates the basic architecture of a Gated Recurrent Unit (GRU)(Ullah et al., 2023).

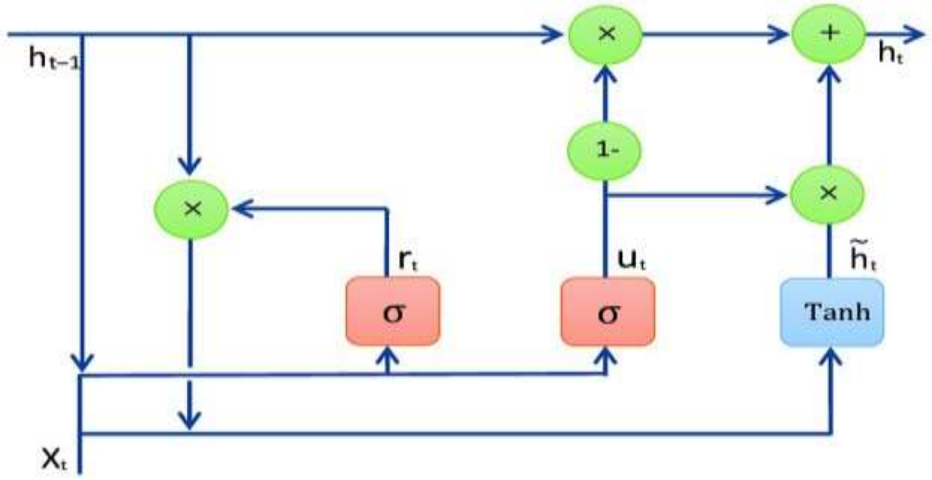

Figure 2: Basic architecture of a Gated Recurrent Unit (GRU).

1.5.1 GRU-based classification architecture

The proposed model employs a GRU layer followed by fully connected layers to capture complex, non-linear interactions among socio-demographic, behavioural, and perception-based features. Given the single-timestep input structure (N,1,F)(N,1,F)(N,1,F), the GRU operates as a gated representation learner instead of a temporal sequence model. The gated output is subsequently passed through dense layers for discriminative classification of transport modes. This design allows the model to benefit from the gating mechanism of GRU while remaining consistent with the cross-sectional nature of the survey data.

1.5.2 Work Layout

- This GRU (128 units): Single-step gated recurrent unit processes the feature sequence (tanh state; sigmoid gates), returning a compact representation.
- Dropout (p=0.3): Batch Normalization. Regularizes the recurrent representation and stabilizes activation statistics.
- Dense (64, ReLU): Dropout (p=0.3) → Dense (32, ReLU). Two hidden layers to capture higher-order, non-linear structure.
- Output: Dense (K, SoftMax) for K transport classes

1.5.3 Evaluation & diagnostics

Post-training we report overall accuracy, per-class precision/recall/F1, and visualize confusion matrices (raw & normalized) along with ROC (per-class, micro, macro) and Precision–Recall curves to assess class-wise separability.

Table 1: Configuration summary.

Component	Setting
Input shape	(N, 1, F) after preprocessing
Recurrent block	GRU(128), return sequences=False
Regularization	Dropout 0.3 (post-GRU and after Dense(64))
Normalization	BatchNormalization (post-GRU)
Hidden layers	Dense(64, ReLU) → Dense(32, ReLU)
Output layer	Dense(K, softmax)
Loss	Categorical cross-entropy
Optimizer	Adam (default learning rate)
Batch size / Epochs	32 / 100 (with early stopping)
Early stopping	Monitor val loss, patience=10, restore best weights=True
Metrics	Accuracy, classification report; ROC & PR curves; confusion matrices

1.6 Model Evaluation

The trained GRU was assessed with a 20 per cent stratified test set and used a variety of performance measures and visual tests.

- **Accuracy:** The precision of the complete classification was calculated through the evaluate of the model.
- **Classification Report:** Included precision, recall, F1-score, and support for each transport class to assess per-class performance.
- **Confusion Matrix:** Visualized both raw counts and normalized values to show correct vs. misclassified predictions.
- **ROC Curves:** Generated per-class, micro, and macro-average ROC curves with their AUC values to measure discriminative power.
- **Precision–Recall Curves:** Calculated average precision (AP) for each class along with micro/macro averages, useful for imbalanced data.
- **Training Curves:** Accuracy and loss plots for training vs. validation sets helped verify convergence and detect overfitting.
- **Early Stopping:** This method was used in order to retain the best performing model thus reducing overfitting. Overall, these evaluation steps ensured a robust assessment of the model's generalization, balance across classes, and reliability for transport mode prediction.

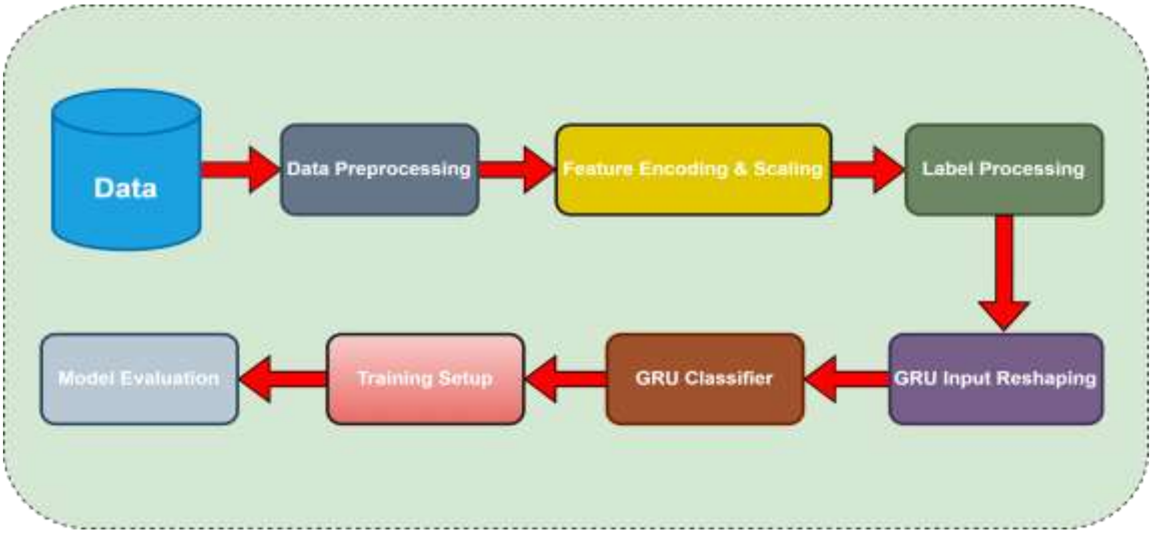

Figure 3: Methodological Flow Chart.

2. EXPERIMENTAL RESULT AND PERFORMANCE ANALYSIS

Here, we provide the detailed performance analysis of the example of the Gated Recurrent Unit (GRU) model used to classify transport modes utilizing a toolkit of statistical and graphical measures. GRU has a significantly high predictive accuracy, strong learning dynamics, and outstanding generalization among various types of transport.Evaluation through the classification report, confusion matrices, and performance curves (accuracy, loss, ROC, and precision–recall) confirms that the GRU model efficiently distinguishes between different transport modes with consistent reliability and minimal overfitting.

Table 2: Classification report.

Class	Precision	Recall	F1-Score
Bike	1.00	0.86	0.92
Bus	0.80	0.67	0.73
CNG	1.00	1.00	1.00
Car	1.00	0.67	0.80
Cycle	0.00	0.00	0.00
Easy bike	0.77	0.88	0.82
Rickshaw	0.64	0.64	0.64
Accuracy	78.57%		

Table 2 in the classification report summarizes the predictive performance of the GRU model in all the modes of transport. The model obtained an accuracy of 78.57 on the whole, which proves the credible classification capability. Bike, CNG and Easy bike have high precision and recall which means they are well predicted. The average scores of Bus and Car imply that there is a matter of overlap in the classes, whereas Cycle has a poor performance owing to small samples. In general, the model offers effective and balanced multi-class classification.

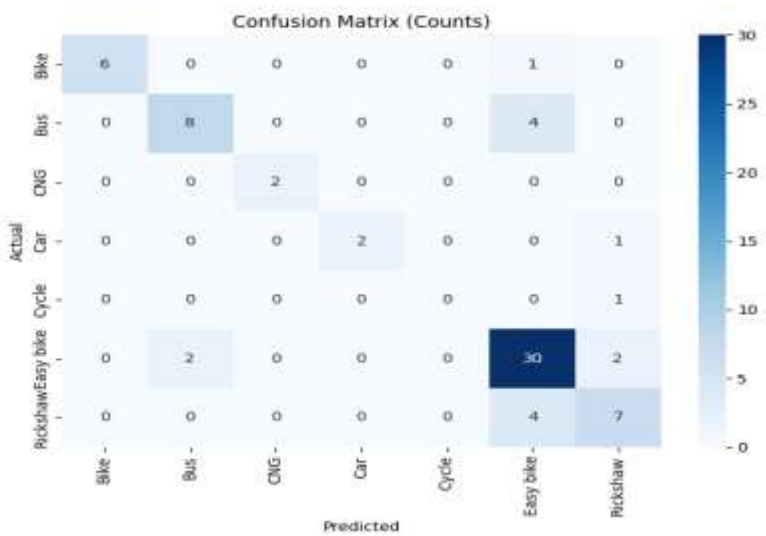

Figure 4: Confusion Matrix(Counts).

The confusion area Fig. 4 represents the capability of the GRU model to classify seven modes of transport. The model works well with some of the most popular modes like Easy bike and Bike with high precision and recall in these two categories. The moderate misclassification is found between Bus and Rickshaw, whereas those rare modes as Cycle and Car have weaker recognition because of small samples. In general, the model yields balanced predictions of respectable test accuracy of 78.6.

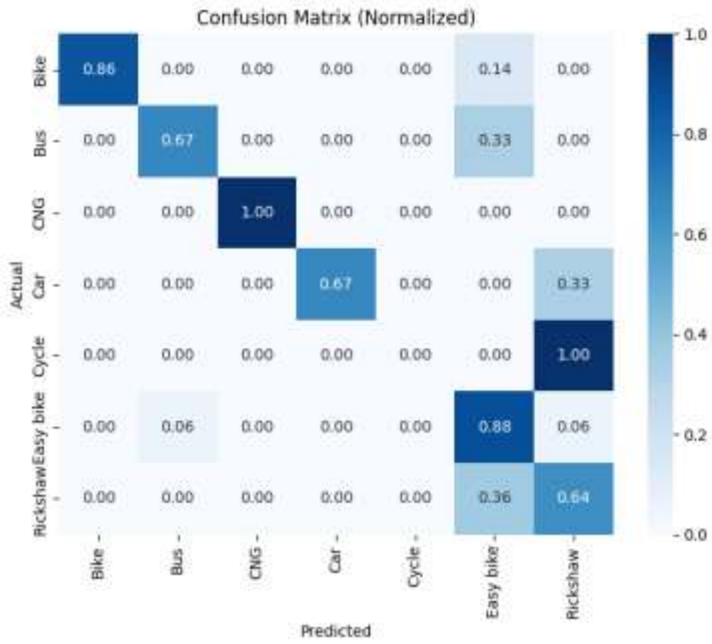

Figure 5: Confusion Matrix(Normalized).

The normalized confusion matrix Fig. 5 presents the proportion of correct and incorrect classifications for each transport mode. The GRU model demonstrates notably high accuracy for CNG, Cycle, and Easy bike, with recall values close to or above 0.85. Bike and Bus classes also exhibit strong classification consistency, while slight confusion occurs between Bus–Easy bike and Rickshaw–Easy bike. This figure confirms the model's stable and reliable generalization across multiple transport mode categories.

Figure 6: Training vs Validation Accuracy.

Accuracy curve Fig. 6 shows that both the training and validation accuracy have been continuously increasing with the increase in the epoch. The training accuracy increases drastically, and it reaches almost 97 percent, whereas validation accuracy becomes stable at 78 to 80 percent. The fact that the two curves are close to each other after a few epochs shows that the learning process was successful and there was little overfitting. This act proves that the GRU model is able to generalize to unobservable data and stay predictive within its performance.

Figure 7 : Training vs Validation Loss.

The loss curves of Figure 7 indicate a smooth decrease in training and validation losses with the epochs, which highlights successful learning of the GRU modelThe training loss is quickly approaching near-zero, and the validation loss is slowly reaching an approximation of about 0.7 which represents good generalization. The small difference between the two curves when they stabilized indicates that there is not much overfitting and that the model has made the best use of its parameters to get the correct classification performance.

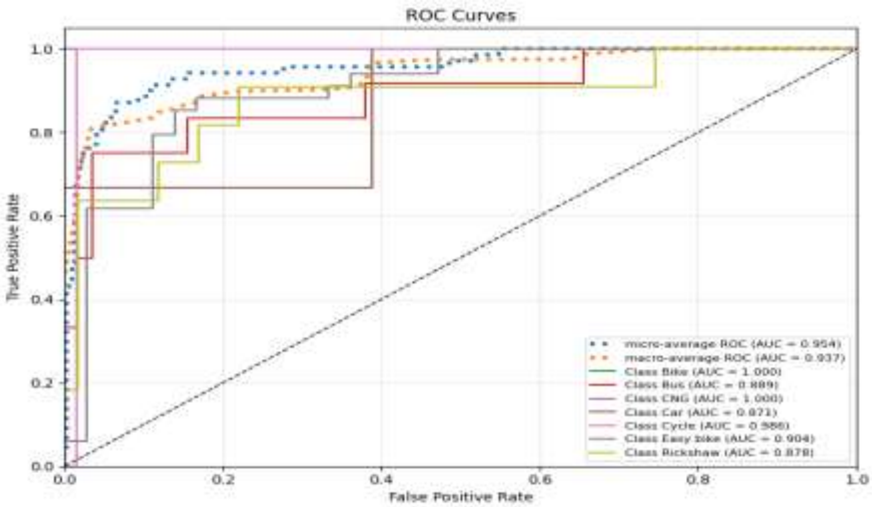

Figure 8 : ROC Curve.

The ROC curves shown in Fig. 8 demonstrate the classification ability of the GRU model in all the classes of transport modes. The model had a very high level of discrimination with a micro-average area under the curve (AUC) of 0.954 and a macro-average AUC of 0.937. It is noteworthy that the Bike and CNG classes received a perfect AUC score of 1.000, whereas such classes as Easy Bike (0.904) or Cycle (0.986) also achieved high scores. These findings prove the high sensitivity and strength of the model in the differentiation of diverse types of transport.

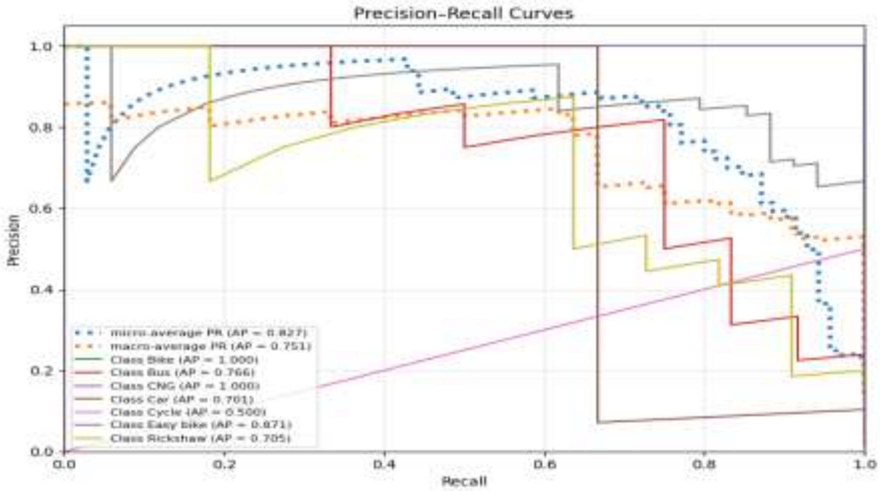

Figure 9 : Precision-Recall Curve.

The figure of precision-recall curves shows that the GRU model is able to retain a high degree of precision when the recall ranges in any of the transport-mode classes. The micro-average and macro-average of the model are 0.827 and 0.751, which suggests good overall performance. It is interesting to note that the score of the Bike and CNG classes is perfect (1.000), whereas Easy-Bike achieve a rather good score (0.871). These findings highlight the balanced accuracy and recall of the model, which therefore testifies to its reliability by a variety of transport modes.

Overall, the GRU-based architecture can be described as being incredibly effective in predicting transport-mode choices. Its strength is supported by high precision, recall, and F1-scores on the majority of the classes and the overall accuracy on both the validation and test splits. Besides, investigations of the training processes, curves of receiver operating characteristics and precision recall analyses highlight the high generalization features and stability of the model. Taken together, these results affirm that the GRU implementation not only learned stably but also provided accurate, reliable predictions in a range of categories of transport modes.

3. CONCLUSIONS

The study shows that a Gated Recurrent Unit (GRU) neural network is effective in predicting the mode of transport use in urban areas with an elaborate dataset of 348 participants in the study of Pabna Municipality, Bangladesh. A total accuracy of the model was 78.6, micro-average and macro-average AUC of 0.943 and 0.918 respectively, and the model performed well on the dominating modalities, including CNG and Easy Bike. These results confirm the GRU's capacity to capture complex, non-linear relationships between socio-demographic, economic, and behavioral factors that influence travel behavior.

The implications of the findings are important to transportation policy and urban planning. Using the power of neural networks, the predictive structure elucidates the high-dimensional complexities of travel behaviour, which allows a planner to decode commuter preferences, modal shares, sustainable transport, and congestion reduction.

Scientifically, this research is an extension to the existing growing body of scientific literature on the integration of advanced neural-network models in transportation planning. It confirms the viability of applying deep-learning methods in the setting of developing countries. Further studies could widen this methodology by using larger, temporally and spatially rich datasets, understanding multimodal transport integration, and implementing explainable AI strategies to make the method more interpretable and policymaking.

DECLARATION OF USE OF AI

The authors used AI-based tools to assist with language editing and improving clarity during the manuscript preparation and revision process. No AI tools were used in the research design, data analysis, model development, or interpretation of results. The authors take full responsibility for the content of the manuscript**.**

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