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DATA-DRIVEN ASSESSMENT OF RICKSHAW TRAFFIC USING COMPUTER VISION IN DHAKA'S CONGESTED CORRIDORS

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ABSTRACT

Rickshaws and autorickshaws have emerged as dominant modes of urban transportation in many developing countries, including Bangladesh. In Dhaka, these vehicles comprise a substantial share of daily mobility. However, their non-standard appearances, irregular shapes, and dynamic movement patterns often result in underrepresentation in traditional traffic data and planning frameworks. This study investigates the application of a custom-trained YOLO (You Only Look Once, version 11n) object detection model to accurately quantify the presence of rickshaws and autorickshaws and to analyze their trends in motorized traffic at major intersections in Dhaka during different traffic periods. A local dataset for training models is developed by capturing and annotating video data in different places of Dhaka city to capture the unique morphological features in the local context. A YOLO model was then trained with data augmentation and hyperparameter optimization, achieving satisfactory performance in terms of mean Average Precision (mAP), precision, and recall, supporting real-time vehicle detection. Using the trained model, rickshaws and autorickshaws counts were extracted across time periods and locations. Analysis of the detection outputs revealed significant temporal and spatial variations in vehicle composition. Rickshaws showed markedly different trends compared to other motorized vehicles, with their presence peaking during specific periods and locations. These findings highlight significant spatial and temporal variations in the presence of rickshaws and autorickshaws compared to other motorized vehicles and demonstrate how AI-powered object detection can uncover nuanced traffic patterns often overlooked in traditional analysis. This enables more data-driven and inclusive transport planning, particularly in rapidly urbanizing cities like Dhaka.

Keywords: *Rickshaw Detection, YOLO Object Detection, Urban Traffic Analysis, Deep Learning in Transportation, Dhaka City Traffic.*

INTRODUCTION

Rickshaws and autorickshaws are widely used urban transport modes in many developing cities, including Dhaka, where they primarily support short-distance and last-mile travel. In dense urban environments such as Dhaka, non-motorized transport particularly cycle rickshaws play a crucial role in providing flexible and affordable daily mobility (UN ESCAP, 2021). The rapid growth of motorized and electric rickshaw variants has increased the complexity of mixed traffic conditions, making accurate and high-resolution data on rickshaw flow and interactions with motorized vehicles essential for effective transport planning (Liu et al., 2022). Despite their importance, rickshaws and autorickshaws are frequently excluded from formal transport data and planning frameworks. This exclusion is largely linked to their informal operation, diverse physical characteristics, and non-standard movement behaviour, which are not adequately captured by conventional, lane-based planning approaches (Hasan & Dávila, 2018). As a result, traditional traffic surveys and analytical methods often fail to represent these modes accurately, leading to their systematic underestimation in traffic assessments and signal design practices (Rahman et al., 2004).Manual traffic counting remains common in developing regions; however, it is labour intensive, prone to human error, and difficult to apply consistently at congested intersections with heterogeneous traffic flows. Similarly, conventional traffic monitoring and control systems are often inadequate in environments dominated by non-motorized and small paratransit vehicles (Tran et al., 2022). These limitations highlight the need for more flexible, automated, and scalable data collection approaches. Recent advances in deep learning and computer vision offer promising alternatives. Convolutional neural network (CNN) based object detection models have demonstrated strong performance in complex visual environments and real-time urban traffic monitoring (Seifert et al., 2017; Zhao et al., 2024). Recent study by Talaat et al. (2025) employed a YOLOv11-based framework for real-time vehicle detection and dynamic traffic flow optimization However, most existing implementations rely on generic datasets and focus on standard motorized vehicles, limiting their effectiveness in detecting locally specific modes such as rickshaws and autorickshaws. Previous studies emphasize that accurate detection in heterogeneous traffic conditions requires locally collected datasets and context-specific model training (Liu et al., 2022). Nevertheless, applications tailored to Dhaka's mixed-traffic context remain limited. This gap motivates the present study, which applies a custom-trained YOLOv11n model using locally annotated video data to detect and analyse rickshaw and autorickshaw activity. The study contributes by: (1) introducing a custom-modified YOLOv11s model; and (2) generating the detailed rickshaw flow for Bangla Motor and Shahbagh, enabling more data-informed transport policies. In this study, the term rickshaw collectively refers to both cycle rickshaws (non-motorized) and auto rickshaws (motorized, including electric variants). This grouping is used for analytical consistency, as both modes operate under similar usage contexts short-distance, flexible, and para-transit services in Dhaka's urban traffic environment.

METHODOLOGY

The main purpose of the study is to understand and evaluate the trend and effect of peak hour on rickshaw volume at intersections using Computer Vision. *Figure 1* shows the workflow diagram of our study which involves (a) collecting video of traffic flows, (b) training a YOLO-based object detector to identify vehicle (rickshaws), (c) extracting hourly counts from the videos, and (d) analysis of the results.

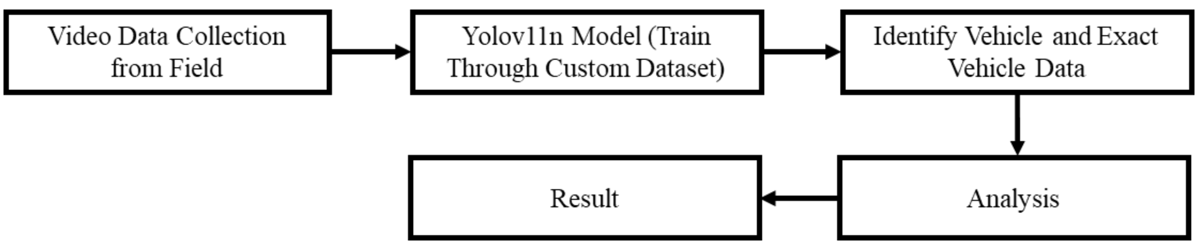

Figure 1: Workflow Diagram

1.1 Study Area

The Bangla Motor-Shahbagh corridor along Kazi Nazrul Islam Avenue is a key urban transportation spine in central Dhaka, carrying heavy mixed traffic throughout the day. Bangla Motor functions primarily as a commercial transit node with three dominant arms connecting Farmgate, Shahbagh, and Moghbazar/Eskaton along with an additional minor leg that sees comparatively lower traffic activity. Frequent bus stopping, roadside commercial activities, and mixed vehicle composition reduce the effective roadway width and create recurrent bottlenecks. Shahbagh, a four-leg intersection surrounded by major educational, cultural, and medical institutions, experiences intense pedestrian movement and continuous multidirectional vehicular flows. Both intersections are traffic police regularly override signals due to irregular turning movements, heterogeneous traffic behaviour, and frequent queue spillover. Consequently, both locations face chronic congestion and operational instability driven by poor lane discipline and high interaction between motorized and non-motorized. Below the *Figure 2* illustrates the Study area map.

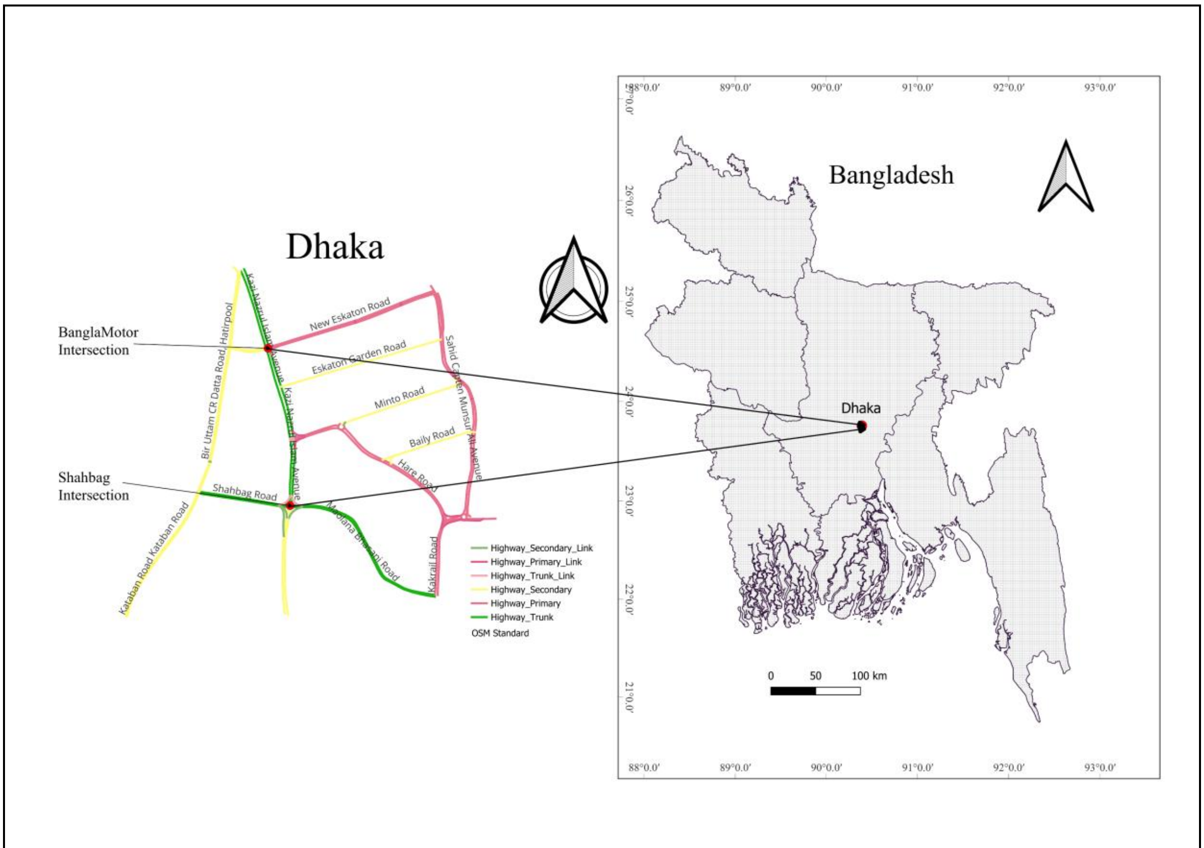

Figure 2 : Study Area Map

1.2 Model Preparation and Training

A custom YOLOv11n model was developed to detect rickshaws accurately within Dhaka's mixed traffic environment using a single-class dataset dedicated solely to rickshaw identification. A dataset of 1,100 locally captured images containing rickshaws in diverse traffic and lighting conditions was compiled to represent the full range of morphological variations found in Dhaka, including differences in canopy colour, passenger load, and background congestion. Manual annotation of all images were performed using the open-source Label Studio tool by drawing bounding boxes around visible rickshaw instances under the single class label "rickshaw." Manual cross-verification of all labelled samples ensured annotation consistency and quality. The annotated dataset was divided into three subsets consisting of 80% training data, 10% validation data, and 10% testing data. Several data augmentation techniques, including random flipping, brightness adjustment, rotation (±15°), and scaling, were applied to enhance robustness to illumination and perspective variability. Model training was conducted on a local computing device over multiple epochs with iterative hyperparameter tuning to adjust batch size, learning rate, and confidence threshold. The final trained model achieved a mean Average Precision (mAP@50) of 0.82, with precision measuring 0.83 and recall measuring 0.74, demonstrating strong detection reliability under complex urban traffic conditions. *Figure 3* illustrates the variation of mAP@50 and overall mAP across the training epochs.

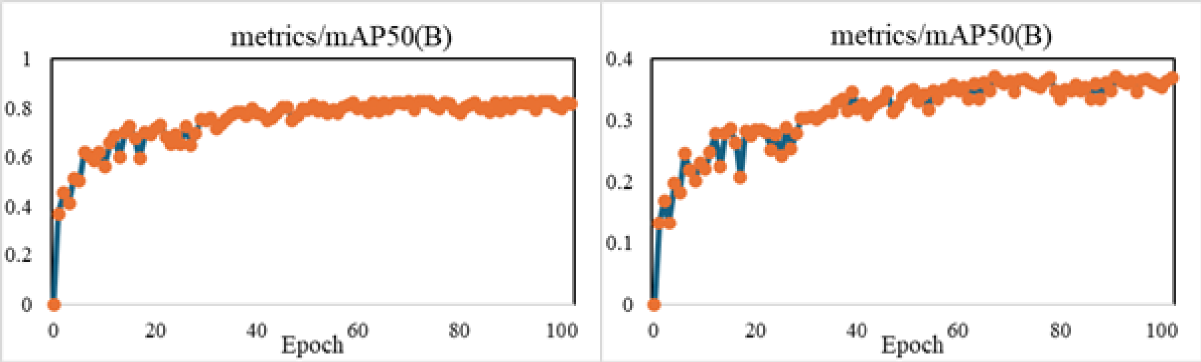

Figure 3: mAP50 and mAP50-95 variation over epoch

1.3 Video Data Collection

Continuous video recordings captured 12 hours of traffic (07:00–19:00) on a regular working day to represent the full diurnal traffic pattern. Multiple mobile phone cameras (1080p, 30 fps) were positioned at elevated locations such as footbridges to ensure complete intersection visibility, with each device recording for 1–1.5 hours at a time. Fixed camera placement maintained consistent framing and field of view throughout the recording period. Segmented hourly video clips facilitated manageable data processing and analysis. Field notes supported verification of traffic conditions and identification of peak-hour periods. *Figure 4* shows the snapshot of collected video data.

Figure 4: Snapshot of video data collected at Bangla Motor Intersection: Kawran Bazar approach (left) and Kathalbagan approach (right)

1.4 Data Extraction

Video analysis was conducted in two stages. Peak-hour detection used a pre-trained YOLOv11n model to assess overall vehicle activity and identify total-vehicle peak periods, which were verified through manual field observations. Rickshaw flow extraction employed the custom single-class YOLOv11n model to detect and count rickshaws on a frame-by-frame basis, with each detection time-stamped using a Python script. Data was exported to CSV format and aggregated to calculate hourly rickshaw volumes (veh/hr). Low-confidence detections (confidence < 0.5) were removed, and consecutive detections of the same object were merged to prevent duplication. The cleaned dataset supported statistical analyses of diurnal variation and peak-hour behaviour.

1.5 Analytical Framework

To analyse the temporal behaviour and flow characteristics of rickshaws, a set of statistical and mathematical methods was used for both descriptive interpretation and inferential testing.

1.5.1 Coefficient of Variation (CV):

CV was used to measure the relative variability of hourly rickshaw flow at each intersection. It enables comparison across sites with different average volumes and is computed as:

$$CV = \left(\frac{\sigma}{\bar{X}}\right) \times 100$$

Where σ is the standard deviation and $\bar{X}$ is the mean hourly rickshaw volume. Higher CV values indicate more variability and temporal irregularity in flow.

1.5.2 Polynomial Regression Model:

A second-order polynomial regression was applied to model the diurnal variation in rickshaw flow:

$$y = at^2 + bt + c$$

Where y is the predicted hourly volume, t is the time (in hours), and a, b, c are least-squares estimated coefficients. This form captures the typical bell-shaped traffic trend over the day.

1.5.3 Coefficient of Determination (R^2)

The goodness of fit of the regression models was evaluated using the coefficient of determination, R^2, defined as:

$$R^2 = 1 - \left[\frac{\sum(yi - \hat{y}i)^2}{\sum(yi - \bar{y})^2}\right]$$

Where y_i is the observed volume, $\hat{y}$ the predicted volume, and $\bar{y}$ the mean volume. An R^2 close to 1 indicates a strong model fit.

1.5.4 Percentage Drop at Peak Hours:

To capture the suppression of rickshaw flow during motorized peak hours, the percentage drop was calculated as:

$$Drop\ (\%) = \left[\frac{(Qpeak - Qobserved)}{Qpeak}\right] \times 100$$

Where:

Where Q_{peak} is the maximum daily rickshaw flow and $Q_{observed}$ the volume during the vehicle peak. A larger drop suggests more disruption to rickshaw activity.

1.5.5 One-Sample T-Test

To test the statistical significance of these reductions, a one-tailed, one-sample t-test was conducted:

$$t = \frac{(\bar{x} - \mu^0)}{(s / \sqrt{n})}$$

Where $\bar{x}$is the mean rickshaw volume during vehicle peak, $\mu_0$is the overall mean, $s$is the sample standard deviation, and $n$is the number of observations. A p-value < 0.05 indicates a significant drop during peak hours.

ANALYSIS AND RESULT

1.6 Data Description

Video data were collected from two major intersections in Dhaka Bangla Motor and Shahbagh which represent central mixed-traffic environments characterized by diverse vehicle types, including private cars, buses, autorickshaws, and a substantial share of non-motorized rickshaws. Continuous daytime recordings (07:00–19:00) were conducted to capture the complete diurnal traffic cycle. The recordings were processed using a custom-trained YOLOv11s object detection model, developed on a locally annotated dataset that reflected the distinct morphological and colour features of Dhaka's rickshaws. The trained model achieved a mean Average Precision (mAP@50) of 0.87 at a confidence threshold of 0.5, ensuring robust and reliable detection performance under varying illumination and occlusion conditions. The processed outputs, hourly vehicle counts were aggregated for each intersection. Field observations were used to determine the total-vehicle peak hours, facilitating a comparative analysis of rickshaw and motorized traffic flow characteristics. *Table 1* presents the observed total-vehicle peak hours.

Table 1: Intersection of total-vehicle peak hours

Intersection	AM Peak	PM Peak
Bangla Motor	09:00–10:00	14:00–15:00
Shahbagh	10:00–11:00	15:00–16:00

1.7 Statistical Analysis

Descriptive statistics were computed to examine the variability and central tendency of rickshaw flows at both intersections. *Table 2* illustrates moderate variability (CV %) across both intersections, which is consistent with non-motorized and para-motorized modes that are sensitive to time-of-day and congestion conditions. Shahbagh exhibited a higher mean flow, reflecting its more consistent operational environment, whereas Bangla Motor experienced relatively greater fluctuation. *Figure 5* illustrates the distribution of hourly rickshaw flow at Bangla Motor and Shahbagh Intersection.

Table 2: Descriptive statistics of hourly rickshaw flow

Intersection	Mean (veh/hr)	Std. Dev.	Coefficient of Variation	Minimum	Maximum
Bangla Motor	725	197.9379	27.31%	469	1052
Shahbagh	869	251.2098	28.90%	351	1183

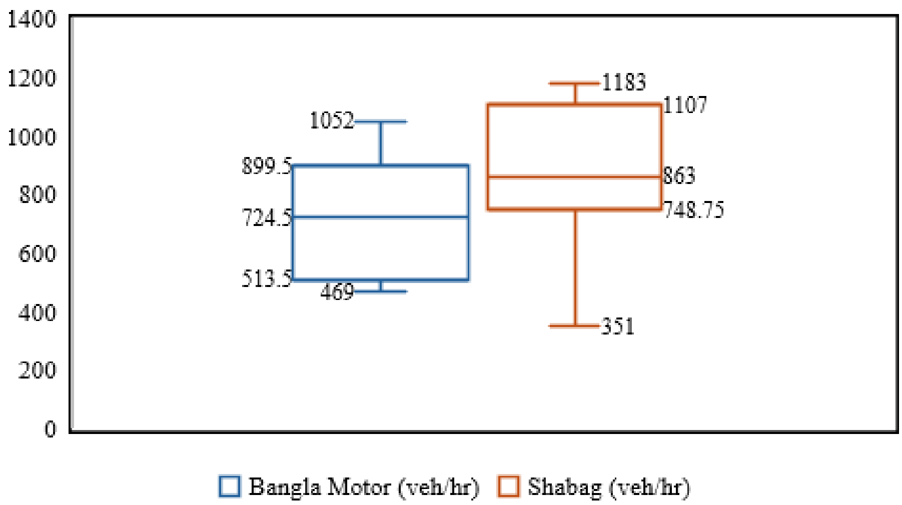

Figure 5: Distribution of hourly rickshaw flow

1.8 Diurnal Flow Pattern Analysis

The diurnal flow profiles exhibited a distinct unimodal distribution at both intersections. Vehicle activity at Bangla Motor and Shahbagh rose gradually from the morning period (07:00–10:00), attaining their respective maxima between 13:00 and 14:00, followed by a gradual decline toward evening. This pattern differs from the bimodal peak of total vehicle traffic in Dhaka, which generally occur earlier in the day (09:00–11:00) and again in the mid-afternoon (14:00–16:00). *Figure 6* illustrates the hourly rickshaw flows, highlighting the gradual increase in the morning, the pronounced midday peak, and the evening decline.

A second-order polynomial regression was applied to the hourly flow data to model these variations:
Bangla Motor: $y = -4.46t^2 + 97.95t + 329.68 (R^2 = 0.60)$
Shahbagh: $y = -19.93t^2 + 279.49t + 131.98 (R^2 = 0.85)$

Both models confirm a curvilinear trend, with peaks occurring around t = 6.5–7 (13:00–14:00), indicating strong midday concentration of flow. The higher coefficient of determination for Shahbagh reflects a more pronounced and predictable diurnal cycle compared to Bangla Motor. The higher coefficient suggests a more predictable, land-use-driven rickshaw pattern, likely influenced by institutional trip generators (universities, hospitals, museums).

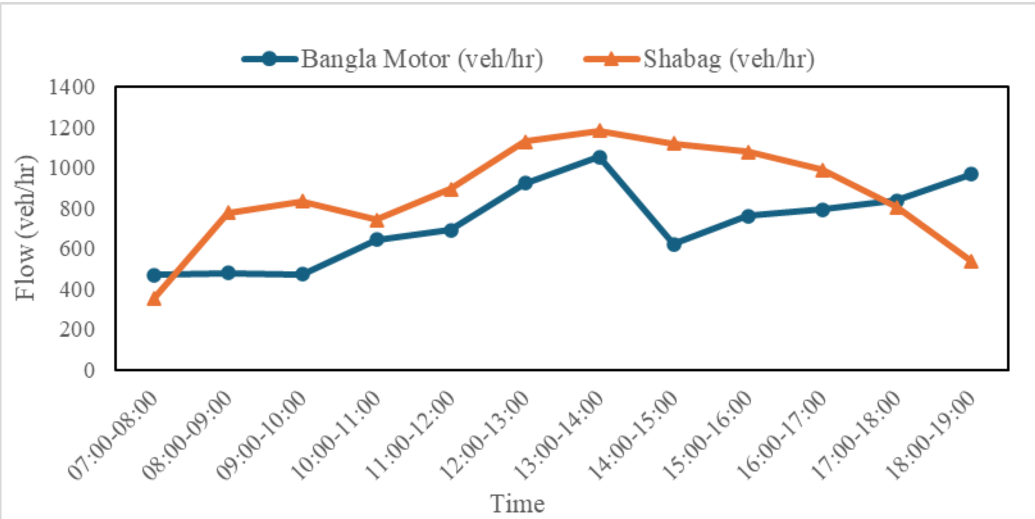

Figure 6: Hourly Rickshaw Flow

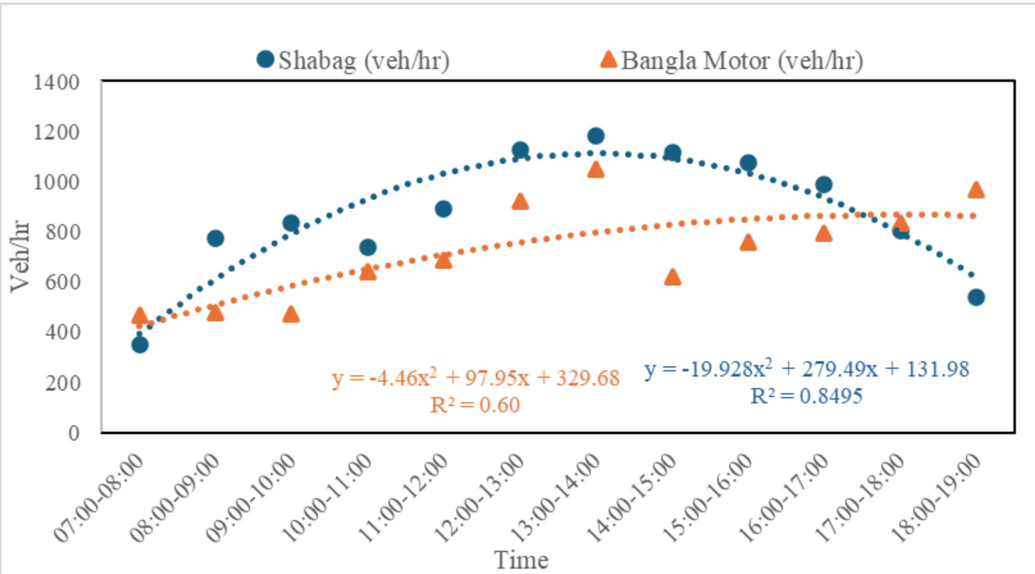

Figure 7: Trendline of Hourly Rickshaw Flow.

Figure 7 illustrates the fitted polynomial trendlines for both intersections, demonstrating synchronized midday peaking and subsequent decline.

1.9 Peak Comparison Analysis

Rickshaw flows during total-vehicle peak hours were compared with their daily maximum and overall average to understand how rickshaw activity differs from motorized traffic patterns. The analysis had two main goals: (1) measurement of the decrease in rickshaw flow during intersection peak hours, and (2) testing whether this decrease is statistically significant compared with the mean hourly flow. Hourly rickshaw counts at both intersections were analysed for the morning (AM) and afternoon (PM) total-vehicle peak periods. The time difference (ΔT) between the total-vehicle peak and the rickshaw peak was calculated to quantify the temporal offset between modes.

Table 3: Comparison of rickshaw flow during total-vehicle peak hours

Intersection	Peak Type	ΔT (hr)	Rickshaw Peak (veh/hr)	Rickshaw at Intersection Peak (veh/hr)	% Drop (from Peak)
Bangla Motor	AM (09:00–10:00)	4	1052	472	55.1 %
Bangla Motor	PM (14:00–15:00)	1	1052	620	41.1 %
Shahbagh	AM (10:00–11:00)	3	1183	740	37.5 %
Shahbagh	PM (15:00–16:00)	2	1183	1077	9.0 %

Table 3 shows that rickshaw flows are much lower during total-vehicle peak hours than at their own mid-day peak.

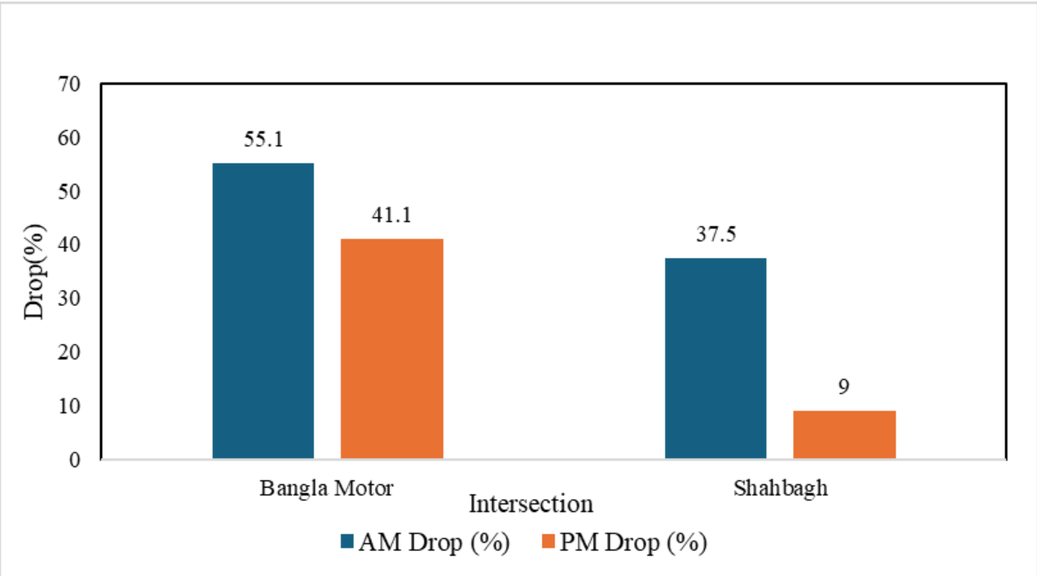

Figure 8: The drop of rickshaw flow in AM and PM Peak period

Figure 8 illustrates the percent drop of rickshaw flow in both AM and PM period. The largest reduction occurred at Bangla Motor (AM), where rickshaw flow dropped by 55 %, followed by a 41 % drop in the PM period. At Shahbagh, the AM flow decreased by 37 %, while the PM flow showed only a small reduction. In all cases, the rickshaw peak occurred about 1 to 4 hours later than the total vehicle peak, indicating a clear temporal separation between the two traffic streams. Overall, the findings underscore a temporal shift between local traffic dynamics and broader vehicular peaks.

Table 4: Statistical test of rickshaw flow suppression (relative to mean hourly flow).

Intersection	Peak Type	Mean (veh/hr)	Observed Peak (veh/hr)	p (one-tailed)
Bangla Motor	AM	724.8	472	0.0005
Bangla Motor	PM	724.8	620	0.0469
Shahbagh	AM	869.3	740	0.0511
Shahbagh	PM	869.3	1077	0.992

From *Table 4*, The t-test results confirm that rickshaw flow reductions at Bangla Motor are statistically significant for both AM and PM peaks ($p < 0.05$). At Shahbagh, the AM decrease was near the significance threshold ($p \approx 0.05$), while the PM value was not significant because rickshaw flow increased during that time. These results indicate that rickshaw activity tends to drop significantly during the hours when motorized traffic volume is highest, particularly at more congested intersections like Bangla Motor.

DISCUSSION

The diurnal analysis shows that rickshaw flow at both Bangla Motor and Shahbagh follows a unimodal pattern, with a clear midday peak between 13:00–14:00, unlike the bimodal peak of total vehicle traffic in Dhaka that occurs earlier in the morning and again in the afternoon. This time difference shows that rickshaw movement follows a different travel rhythm, shaped by local activity patterns and land use rather than by citywide commuter flows. Previous studies found that non-motorized and paratransit trips in Dhaka primarily serve short, local, and access-based travel (Hossain & Susilo, 2011). This causes the peak to be later than formal motorized traffic. The regression models confirm this trend. The higher R^2 value at Shahbagh (0.85) compared to Bangla Motor (0.60) indicates a more regular and land-use-driven rickshaw flow. Shahbagh's surrounding universities, hospitals, and museums are strong trip generators that create steady demand throughout the day. Hossain and Susilo (2011) reported that rickshaws are the most used mode for short institutional and shopping trips in Dhaka, while Rahman and Baker (2018) found that accessibility to such facilities strongly influences modal choice. The predictable pattern at Shahbagh therefore reflects institutional land-use effects on non-motorized mobility. The peak comparison analysis also reveals that rickshaw flow drops sharply during motorized-vehicle peaks, especially at Bangla Motor, where the reduction reached 55% in the morning and 41% in the afternoon. The statistical test confirmed these decreases are significant ($p < 0.05$). This agrees with earlier findings that high traffic volumes and mixed-flow conditions limit intersection performance by reducing discharge rates and capacity during peak periods (Rahman, Okura, & Nakamura, 2004). Also showed that rickshaws reduce intersection capacity and this, forcing a temporary withdrawal from main roads. In contrast, Shahbagh showed only a small reduction (9%) during the afternoon, and the t-test result was not significant ($p = 0.992$). This indicates that rickshaw demand remains stable in institutional areas even when motorized traffic is high. This stability is consistent with prior findings that rickshaws are widely used for education-related trips in Dhaka, serving as the dominant mode for home–education travel (42%) (Hasan & Dávila, 2018). These results highlight that rickshaw movement is not random but strongly related to location-specific land-use characteristics. Overall, the findings confirm that rickshaw flow peaks later than formal motorized traffic (ΔT = 1- 4 hours), showing a clear temporal separation between the two modes. This separation results from different trip purposes and policy pressures. Studies have shown that while motorized mobility is prioritized in Dhaka's transport policy, rickshaws continue to play an essential role in short-distance and low-income mobility, especially in dense urban areas (Begum & Sen, 2004; Cervero & Golub, 2007). The strong midday peak and sustained flow in institutional areas indicate that rickshaws remain a vital component of urban accessibility despite restrictions and congestion pressures.

CONCLUSION, LIMITATIONS, AND RECOMMENDATIONS

This study used computer vision to measure rickshaw movement at two busy intersections in Dhaka and to see how it changes during the day. The results showed that rickshaw flow does not follow the same pattern as motorized traffic. Rickshaw is highest around midday because most rickshaw trips are short and connected to daily activities like school, shopping, and errands. During the morning and afternoon peak hours of motorized vehicles, rickshaw flow becomes much lower, especially at Bangla Motor, where the drop was statistically significant. This means rickshaws and motorized vehicles do not compete for the road at the same time, and they follow different time-of-day needs. This study has some limitations. Only two intersections were used, so the results may not represent all of Dhaka. The analysis was done for one working day only, so weekend or seasonal patterns were not included. The video detection model counted rickshaws accurately, but very crowded or rainy conditions may reduce accuracy. Based on the results, traffic planning in Dhaka should not treat rickshaws and motorized traffic as one pattern. Since rickshaw demand is highest at midday, not during office peaks, rickshaw restrictions should be reviewed carefully instead of applying the same rules at all times of the day. Intersection design, lane management, and signal control should consider the different timing of slow and fast modes. Future studies can improve this work by studying more locations, using longer time periods, comparing weekdays and weekends, and testing how weather or policy changes affect rickshaw flow. More robust Computer Vision model can also be used to study other informal transport modes, such as auto-rickshaws or vans, to build a larger transport dataset for Dhaka.

DECLARATION OF USE OF AI

The authors acknowledge the use of artificial intelligence (AI) tools in the preparation of this manuscript. AI tools (ChatGPT 5.1) were used solely for language refinement, including improvement of grammar, clarity, and readability. All intellectual content, including research design, data collection, data analysis, interpretation of results, and conclusions was fully developed and verified by the authors. All AI-assisted text was thoroughly reviewed and edited by the authors to ensure accuracy and compliance with scholarly standards. No AI tools were used in conducting the research or generating original scientific content.

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