RESEARCH ARTICLE

Analysis of Bus Stop Infrastructure Using Deep Learning-Based Object Detection: A Case of Thrissur, Kerala, India

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Abstract

Bus transport forms the most critical and widely used component of the public road transportation system in India. Bus stops are therefore the most critical nodes connecting passengers to this system. Using a deep learning-based object detection model, this research provides a detailed analysis of the bus stop infrastructure in Thrissur, Kerala, India. The model is applied to a custom dataset of 400 field and Google Street View (GSV) images, and a comprehensive audit is conducted of 80 stops, benchmarking them against Indian road development standards. The findings reveal a large difference in time cost between the methods and demonstrate a highly reliable deep learning-based object detection system. In parallel, a 'de facto' barrier is identified: a clear spatial inequality between the urban core and the periphery systematically excludes accessibility-dependent groups from safe and equitable access to public transport. Crucially, a 'Modern but Inaccessible' paradox was observed: 100% of surveyed bus stops had roof shelters, yet only 2.5% complied with fundamental accessibility standards, a critical failure seen even in the newest structures. This study concludes that deep learning models such as YOLOv8 are among the most effective (recall of 75.3%, precision of 71.7%) and time-efficient (about 15 seconds to survey 80 bus stops after initial development) methods for large-scale urban infrastructural analysis.

Keywords: bus stop infrastructure, deep learning, object detection, universal design, urban transportation.

1 Introduction

The public transportation system is one of the most significant backbones of the sustainable urban mobility sector. Although traditionally defined as any form of passenger or freight transport available for hire or reward, in practice it usually refers to land-based passenger transport [1]. The most basic and critical nodes of these land-based systems are the bus stops, i.e., a place where a bus stops to allow passengers to get on and off [2]. Multiple factors of a bus stop's basic infrastructure make it more comfortable, accessible, and safe for use by different groups of people, including its design, quality, and quantity.

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Bus stops have emerged as a standard case for urban infrastructure detection in research due to their functional importance in transit networks and their visual distinctiveness for computer vision models [3]. In this context, various regulatory bodies in India control and outline the minimum requirements and standards to be followed when designing a bus stop, such as the Ministry of Road Transport and Highways of India (MoRTH) and the Indian Roads Congress (IRC). Despite this, even in urban centres, compliance with these standards is consistently found to be inadequate or non-existent.

In the state of Kerala, India, the high and dense network of bus stops forms a crucial backbone of the public transportation sector. However, most of these stops still lack modern infrastructural qualities and amenities that are essential for commuters, leading to key accessibility and safety concerns. Conducting manual audits to document, assess, and analyse them is a very resource-intensive process that requires extensive time, cost, and manpower, which in turn makes frequent evaluations impractical. In this context, artificial intelligence emerges as a scalable and efficient alternative: it enables automated assessments when provided with a reliable database and robust detection models.

Advancements in computer vision and deep learning have enabled more robust and automated identification of urban infrastructural elements using street-level imagery. Despite these benefits and a growing interest in AI-based urban infrastructure analysis, a notable research gap remains in applying these methods to the complex Indian environment, particularly in heterogeneous and semi-formal contexts such as Kerala. Addressing this gap is crucial for two main reasons: operational efficiency (by reducing cost and time) and user benefit (compliance checks can improve commuter experience and safety). Previous studies have applied GSV imagery and deep learning to a range of urban infrastructure assessments—from bus shelter compliance in developed cities [3] to broader urban morphology and informal settlement mapping [4]—demonstrating the scalability of street-view-based remote analysis. This study addresses the gap by applying AI-based deep learning tools to Indian urban scenarios. Manual observation, GSV-based deep learning, and on-site image-based deep learning were the three approaches used to obtain the most accurate results. Street-view-based deep learning has been tested in several studies across different urban infrastructure types; for bus shelters specifically, their distinct visual features—such as roofs, seating, lighting, and access—make them well-suited targets for automated visual detection [3], while parallel work has demonstrated the method's transferability to other urban mapping contexts [4].

Hence, the main research question addressed in this study is: *How do AI-driven object detection tools compare with manual observation in assessing the compliance of infrastructural elements with standards?* This helps evaluate the efficacy of AI-driven deep learning models for assessing the compliance of bus stop infrastructure against traditional manual audits. A comparative foundation is created by studying the guidelines and developing a comprehensive, geo-located dataset of bus stops through a manual audit and GSV. Deep learning models are then used on this dataset to recognise spatial attributes and measure compliance in the same areas, and finally the results are compared against the manual 'ground-truth survey' to refine the hybrid audit process (see Figure 1 for the complete methodology).

This research focuses primarily on the key spatial characteristics identified by MoRTH and IRC and their visual analysis across six major roads within a 10 km radius of Swaraj Round, the main city centre of Thrissur; these roads do not include inner and rural roads. Incomplete bus stop mapping and a limited sample size due to time constraints, combined with limitations in the image quality of both GSV and field photographs, restrict the accuracy of AI-based measurements. This necessitates the use of high-resolution imaging and manual detail mapping. Dimensional analysis tools, which rely on a set of established reference factors, often carry uncertainty in exact dimensions; further field calibration is therefore required, which, in this study, was not performed due to time constraints.

This research aims to combine manual field observations, references to the standards, and deep learning-based object detection models to analyse bus stop infrastructure in Kerala. Several methods and benchmarking standards are compared to achieve the highest accuracy and precision. Section 2 reviews recent literature; Section 3 details the methodology; Section 4 presents the analysis; Section 5 compiles the results and discussion; and Section 6 reports the conclusions.

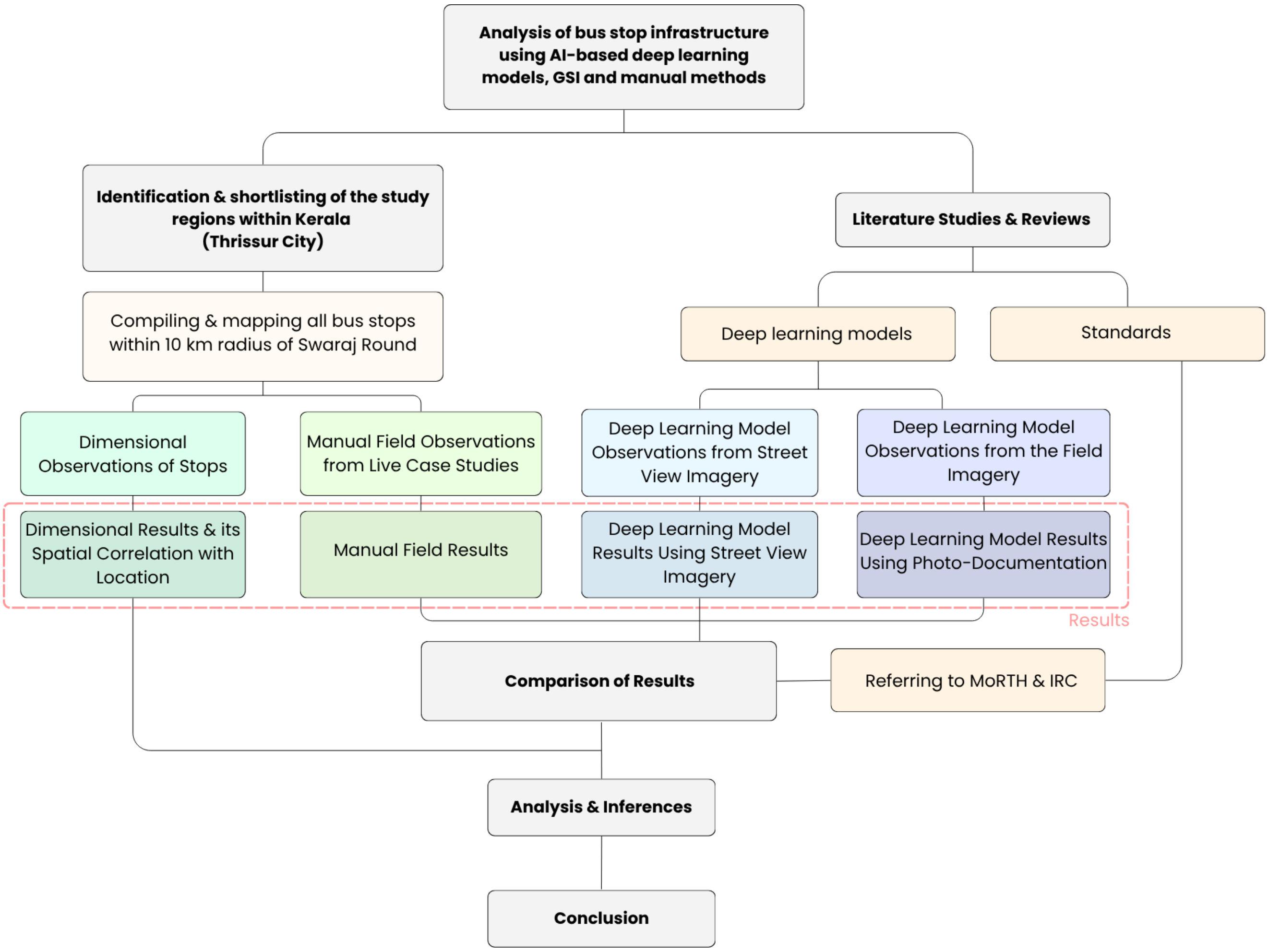

Figure 1. Overall research methodology combining AI-based deep learning models, GSV, and manual field methods.

Table 1. Representative bus dimensions [5–7].

Operator	Model	Length (mm)	Width (mm)	Height (mm)	Gnd. Cl. (mm)
KSRTC (low floor)	Volvo 8400	12000	2510	2300	190
KSRTC (Swift)	Ashok Leyland Viking VK2011	11187	2550	–	250
Private	Tata Starbus City	8630	2340	2910	–
Private	Intercity Bus	12000	2550	–	–

2 Literature Review

In Kerala, public transportation by bus constitutes one of the densest and most heavily patronised transit networks in the country. Roads play a more prominent role than other modes of transport, mainly owing to the state's geographic peculiarities and scattered habitation. There is a comparatively smaller rural–urban divide, and the geographic area is limited to 38,863 km^2, with a total fleet of 25,449 buses, of which 19,496 are private buses (77%) and 5,953 are KSRTC buses (23%). Private buses dominate all districts of Kerala except Thiruvananthapuram [8]. Beyond their operational role, bus shelters have been recognised in recent literature as multifunctional urban elements with potential as resilient infrastructure extending beyond mere transit utility [9]. Representative bus dimensions relevant to bay and kerb design are summarised in Table 1.

2.1 Survey Methods

2.1.1 Traditional methods of bus stop survey

Traditional methods employ procedures such as on-site field surveys and checklists. This helps to understand and assess bus stops in real time and provides accurate data on current conditions, which is its primary benefit. However, such methods are time-consuming, costly, and labour-intensive when large assessment areas are involved.

2.1.2 *Digital and remote survey methods*

The emergence of GSV and other street-view imagery tools, along with their wide availability, has transformed traditional methods into large-scale, low-cost, remote audits of urban infrastructure—in this case, bus stops and shelters. Although powerful, these tools have documented limitations, such as potential image occlusion, outdated street-view images (SVI), and inconsistent coverage, which can reduce reliability across diverse urban mapping applications [3, 4].

2.1.3 *AI and deep learning in urban studies*

AI and deep learning work together, especially in computer-vision-based object detection, to automate and accelerate the analysis of digital imagery of the urban fabric. Computational modules also assist in producing fast and simple dimensional estimates. These tools bring speed, scalability, and objectivity to identifying urban infrastructure. However, the output still requires human verification and contextual understanding to ensure that detected features comply with the standards, and the correlations must be examined manually by comparing outputs and datasets [3].

2.2 Standards

2.2.1 *MoRTH standards and guidelines for bus stops*

The Ministry of Road Transport and Highways (MoRTH) is an apex organisation under the Central Government, entrusted with formulating and administering—in consultation with other central ministries/departments, state governments/UT administrations, organisations, and individuals—policies for road transport, national highways, and transport research, with a view to increasing the mobility and efficiency of the country's road transport system. The Ministry has two wings: the Roads wing and the Transport wing [10]. MoRTH provides "Accessibility Guidelines for Bus Terminals and Bus Stops," which ensure universal access for people with disabilities and other vulnerable groups [11]. These guidelines cover all aspects of designing and planning bus terminals and stops and aim to create an inclusive environment. They detail the requirements of a bus stop, which also serve as the parameters of this study, as shown in Table 2.

2.2.2 *IRC guidelines*

The IRC was set up by the Government of India in consultation with the state governments. Established in December 1934, it is the premier body of highways engineers in India. Its principal objectives include providing a national forum for pooling experience and ideas on the construction and maintenance of highways and recommending standard specifications; it also provides a platform for professional opinion on issues relating to roads and road transport. The codes used in this study are: IRC 35 (1970, revised 2015); IRC 80 (1981); IRC SP 73 (2007, revised 2018); IRC SP 84 (2014, updated 2019); and IRC 103 (2012) [12–16]. These standards detail the requirements and parameters of the study, as shown in Table 3.

3 Methodology

3.1 Study Area

The geographic focus of this study is the city of Thrissur, Kerala. The city was selected because of its designation as a key transit hub and its recent infrastructural developments, including new bus shelters constructed under the UNESCO Learning City programme (Thrissur was designated a UNESCO Learning City in 2021), which make it a highly pertinent case study. The study area was defined as a 10 km radius originating from the city's central landmark, Swaraj Round. To ensure comprehensive coverage of the public transit corridor, six primary arterial routes—towards Athani (North), Permangalam (North-West), Arimbur (South-West), Thayamkulamkara (South), Thalore (South-East), and Mannuthy (East)—diverging from Swaraj Round were selected for analysis. These routes represent the primary corridors of public transit in and out of Thrissur, extending from the urban core to the periphery.

3.2 Data and Methods

3.2.1 *Identification, mapping, and documentation of bus stops*

The initial stage consisted of identifying and spatially mapping 80 bus stops along the selected routes using a combination of GSV imagery and on-site documentation, with precise coordinates recorded for each. This dual-method approach was employed to build a comprehensive visual dataset. A total of 400 images were collected: 200 high-resolution field photographs (captured in 2025) and 200 GSV images (from 2023–2024). The field images were captured

Table 2. MoRTH standards and parameters used in this research.

Parameter	Specification
Stop length and width	Width = 2 wheelchair widths; length painted in a distinctive colour
Ramp and accessibility	Bay $\geq$ 400 mm; ramp = 1:8; width = 1200–1540 mm
Kerb	Height 140 mm; smooth, angled-face kerbs
Seating	Reservation and symbols for differently abled users
Signage	Braille info panels for the visually impaired; double-sided; illuminated/reflectorised for night visibility
Lighting	Adequate levels for safety
Litter bin	Minimal nuisance and obstruction to movement
Drainage	Adequate provision for safety
Green infrastructure	Presence needed
Emergency/contact assistance	Police call boxes

Table 3. IRC standards and parameters used in this research.

Parameter	Specification
Bus bay	Length $\geq$ 15 m
Location	Staggered on opposite sides of a junction to avoid congestion; away from structures $\geq$ 3 m high; $\geq$ 30 m from intersections
Layout	Setback $\geq$ 0.25 m
Physical shelter	Protection from sun, wind, rain, etc.
Drainage	Proper cross-slope for drainage
Landscape	Landscape treatment
Kerb	Height should match the bus floor height
Lighting	Adequate illuminance for safety
Accessibility	Guide blocks; covered steps; step rise $\leq$ 150 mm and width $\geq$ 5 m; ramp width $\geq$ 1 m
Pavement	Marking of pavement and of 'BUS STOP'
Guard rails	Pedestrian guardrails on either side of the ramp
Road marking	Markings to indicate the stop
Lane marking	Visibility marking at 150 m intervals; white solid line; width $\geq$ 3 m
Footpath	Width 3 m

with a Samsung Galaxy S22 Ultra with a 108 MP main rear camera (Samsung S5KHM3 sensor, 1/1.33 inch), a 12 MP ultrawide camera (Sony IMX563 sensor, 1/2.55 inch), and a 10 MP telephoto (3×) camera (Sony IMX754 sensor, 1/3.52 inch) [17].

3.2.2 *Database creation using Roboflow and training with YOLOv8*

To manage the visual dataset, this study used Roboflow, a widely used platform that provides tools for building and deploying computer-vision models, including data labelling, model training, and model deployment, alongside Ultralytics tools [18]. A database of 400 images was uploaded and preprocessed for annotation, and separate classes were created for each of the eighteen components (Table 4). The dataset was partitioned into a standard 70% training (280 images), 20% validation (80 images), and 10% testing (40 images). For object detection, the YOLOv8 (You Only Look Once, version 8) algorithm was deployed. YOLOv8 was released by Ultralytics and offers state-of-the-art accuracy and speed; building on previous YOLO versions [19], it introduces features and optimisations suited to a wide range of object detection tasks [20]. The model was trained locally on the annotated dataset to identify and classify the features listed above.

3.2.3 *Model validation*

To assess the model's performance, standard metrics were computed: precision, recall, mean Average Precision (mAP), and the F1 score. Precision is the fraction of predicted positives that are correct, $\mathrm{Precision} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FP})$; recall is the fraction of actual positives that are detected, $\mathrm{Recall} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FN})$; and the F1 score is their harmonic mean, $F_1 = 2\,\mathrm{Precision}\cdot\mathrm{Recall}/(\mathrm{Precision}+\mathrm{Recall})$, which balances false negatives and false positives [21]. When there are more than two classes, overall accuracy alone does not reveal per-class performance, so precision and recall are preferred.

Table 4. Classes and their instance counts in Roboflow.

Class	Count
Ad	139
Ad-board	83
Bus-stop	575
CCTV	57
Charging-port	59
Dust-bin	63
Emergency-numbers	61
Info-board	53
Light	56
Post-box	6
Posters	124
Ramp	10
Roof	575
Seat	584
Speaker	27
Step	77
Stop-sign	77
Vegetation	105

In addition, human–model agreement was assessed to quantify the consistency between manual and model-generated annotations. Kappa statistics are frequently used to test inter-rater reliability. Cohen's kappa was designed to account for the possibility that raters agree by chance; although widely used, it has known limitations as documented in the literature [22]. Cohen's kappa was initially considered here, but it proved impractical because it fails under class imbalance and prevalence effects, producing paradoxically low or negative values despite high observed agreement. For this reason, Gwet's AC1 [23] was used instead, as it provides a more stable inter-rater reliability coefficient that is less affected by prevalence and marginal probability than Cohen's kappa [24].

3.2.4 *Dimensional analysis using Fiji/ImageJ*

A quantitative dimensional analysis was also conducted on the image database to extract the physical measurements of the bus stop infrastructure. The Fiji distribution of ImageJ was used; Fiji is a pre-packaged version of ImageJ configured with numerous useful plugins and can open image files from nearly any camera/microscope software [25]. To establish a reliable scale across all photographs, known reference dimensions such as the standard average Indian female height (152 cm) [26], charging ports (9 cm), and CCTV cameras (12 cm) were used as reference points. This workflow was carried out for straight-on images (within $\pm 30°$) as well as high oblique views, to recover dimensions in the z and y axes. The process yielded measurements for the key structural elements—overall shelter height, internal clear height, and seat height—which were benchmarked against established standards and used to analyse the correlation between a stop's location and its size.

4 Analysis

The estimated time required for each of the three methods is summarised in Table 5, and a step-by-step comparison of the three methodological paths is given in Table 6.

5 Results and Discussion

5.1 Deep learning-based object detection results

To quantify the robustness of the model, its performance metrics were evaluated: precision, recall, mAP@50, mAP@50–95, and F1 score. The values were: precision 0.7173, recall 0.7531, mAP@50 0.7346, mAP@50–95 0.5222, and F1 0.7347 (Figure 4). The F1, mAP@50, and recall values indicate that the model reliably detects and distinguishes urban infrastructural features across multiple classes. The mAP@50 of 0.7346 supports strong detection capability, whereas the mAP@50–95 of 0.5222 shows a performance drop under stricter IoU thresholds, suggesting limitations in fine-grained localisation. The model detects approximately 75.3% of the actual objects (recall) and, of the detected objects, approximately 71.7% are correct (precision). Representative detections are shown in Figure 5. A confusion matrix was developed to quantify class-based performance (Figures 2 and 3). Classes such as bus stops (50 instances; 98% recall) and roofs (48 instances; 91.7% recall) show strong diagonal dominance, indicating a high true-positive rate, likely because they are large and consistently repeated. In contrast, smaller amenities such as seats (40 instances; 12 false positives; 12 false negatives; 76.9% recall) show higher variance, likely due to occlusion, environmental factors, class imbalance, annotation ambiguity, or feature similarity. The human–model agreement, quantified using Gwet's AC1, was computed per class, with values ranging from 0.551 to 1, indicating moderate to near-perfect agreement depending on the class (Figure 6). These results indicate consistent model performance in identifying and categorising major bus stop amenities, and show that agreement is class-dependent rather than uniformly strong.

Table 5. Initial time taken for each method.

Method	Task / component step	Time (h)
Traditional survey	Field travel and logistics (80 stops)	9.3
	On-site survey (80 stops)	16
	Total	**25.3**
Digital (GSV) survey	Virtual "travel" (finding 80 stops)	2.5
	Virtual survey (80 stops)	8
	Total	**10.5**
AI (YOLOv8) method	Data curation (upload 400 images)	2
	Data annotation (400 images, 18 classes)	8
	Quality check (QC)	2.5
	Preprocessing (Roboflow augmentations)	0.5
	Model training (YOLOv8)	1.5
	Review and iteration	3
	Total development	**17.5**

Table 6. Comparative procedures across the three methodological paths.

Procedure	Traditional method	Digital / remote (GSV)	AI deep-learning model
Literature study	Manual/digital versions of standards	Digital versions of standards for review	Review of academic papers on computer vision and object detection
Data collection	Standards from MoRTH and IRC	—	—
Site study	Dataset/checklist creation from MoRTH and IRC standards	On-site survey and checklist from the standards	Virtual survey using GSV; amenity list from the standards; automated detection by class
Condition assessment	Photos and checklist mark-off of amenities	Selected GSV images used to mark amenities	Detection results quantify parameters against guidelines
Analysis	Manual notes compared with guidelines	Analysis of conditional-assessment results	Automated assessment gives a rapid overview of all parameters
Observations	Qualitative and quantitative notes vs. standards	Geotagged photos and notes in structured spreadsheets vs. standards	Structured data with bounding boxes, class labels, and confidence scores vs. standards

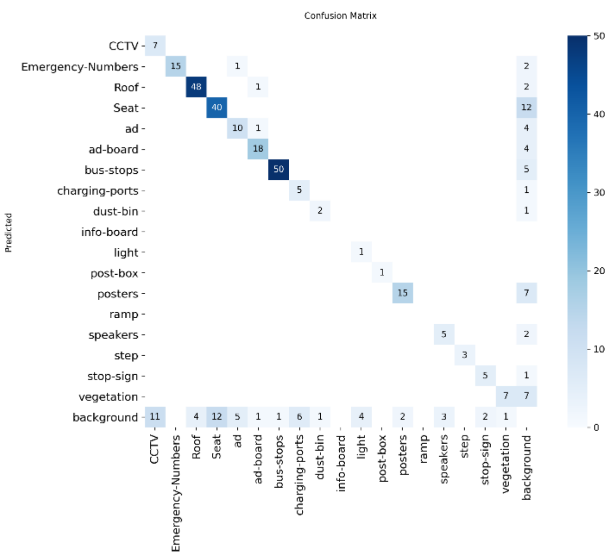

Figure 2. Confusion matrix of the YOLOv8 detector (absolute counts).

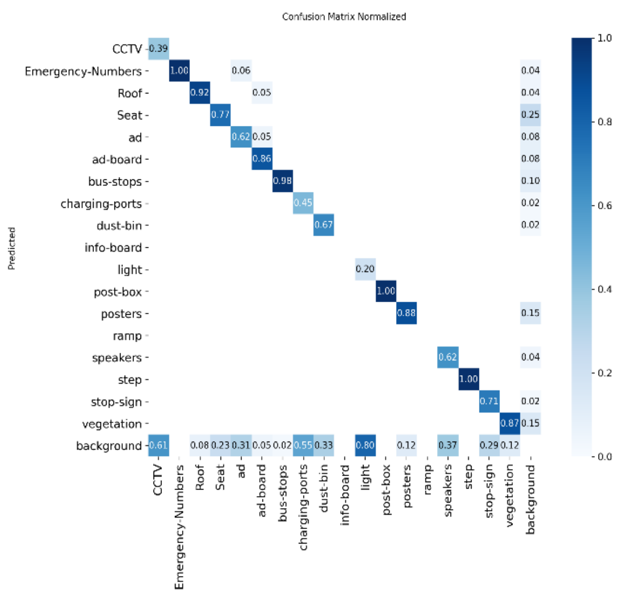

Figure 3. Normalised confusion matrix of the YOLOv8 detector (per-class recall).

5.2 Compliance results

The analysis of the 80 bus stops revealed strong provision of basic shelter infrastructure but significant deficits in modern amenities and an almost complete absence of accessibility features. All 80 surveyed

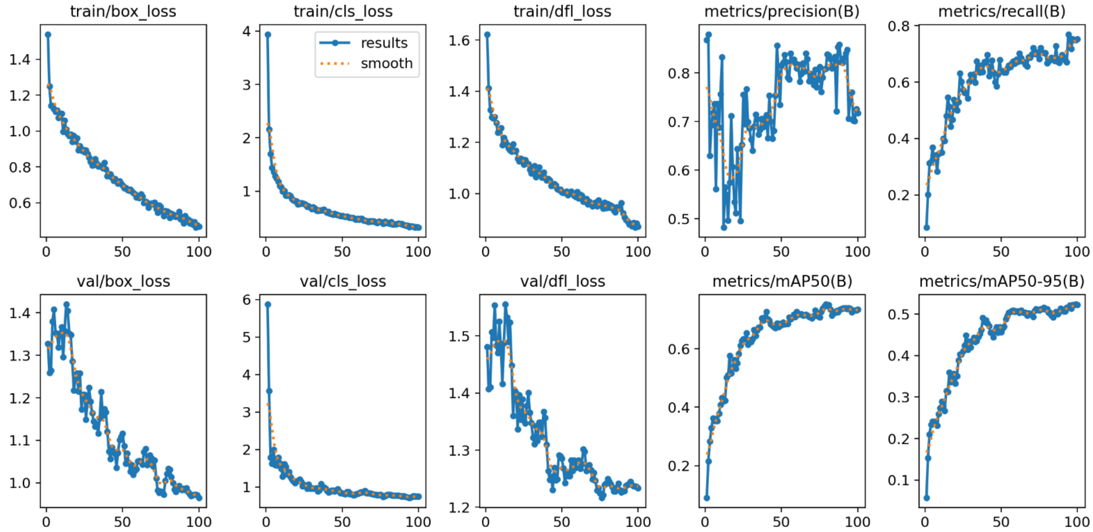

Figure 4. YOLOv8 training and validation curves (losses and metrics over 100 epochs).

Figure 5. Sample YOLOv8 detections on field images, with class labels and confidence scores.

locations had an overhead roof/shelter (100%), and 64 stops (80%) had seating. However, only the newly constructed shelters under the UNESCO initiative (9 stops) featured an extensive suite of modern amenities such as integrated lighting, emergency numbers, CCTV, signage, speakers, and charging ports. Crucially, the research revealed systemic non-compliance with national standards, especially regarding accessibility: only 2 of the 80 stops (2.5%) had ramps, and of these only one was functional (the other was still under construction), reducing effective provision to one stop in 80 (1.25%). Both ramp stops were along the North (Athani) route and were not part of the UNESCO initiative, showing that even the most modern installations fail to meet universal-design requirements. The most basic public amenities were also rare: waste bins at only 2 of 80 stops (2.5%) and dedicated handrails at 3 of 80 stops (3.75%). This single accessible stop is shown in the centre panel of Figure 7.

5.3 Spatial correlation of dimensions to location

A strong spatial correlation was observed between a stop's location and its physical dimensions, revealing a clear infrastructural hierarchy (Figure 7). The most recent and largest UNESCO-programme stops were concentrated around Swaraj Round; the lengths of these shelters ranged from 600 to 750 cm and their overall height (including digital billboards) from 500 to 600 cm. Within a 2–3 km radius of the centre, smaller versions were found, with lengths of about 550–650 cm and heights of about 400–500 cm (including printed advertising boards). Beyond this threshold, both the quality and scale of the infrastructure declined; near the 10 km mark, most shelters became rudimentary concrete structures of small and varied sizes. A notable exception is the Athani route, which shows comparatively higher-quality amenities regardless of distance from the centre.

5.4 Discussion

This study reveals a clear trade-off between the initial cost and the long-term scalability of the three methods (Table 5). The traditional on-site method was the most resource-intensive, requiring an estimated 25.3 h to survey and analyse 80 stops, largely due to physical travel and site documentation. The digital (GSV)

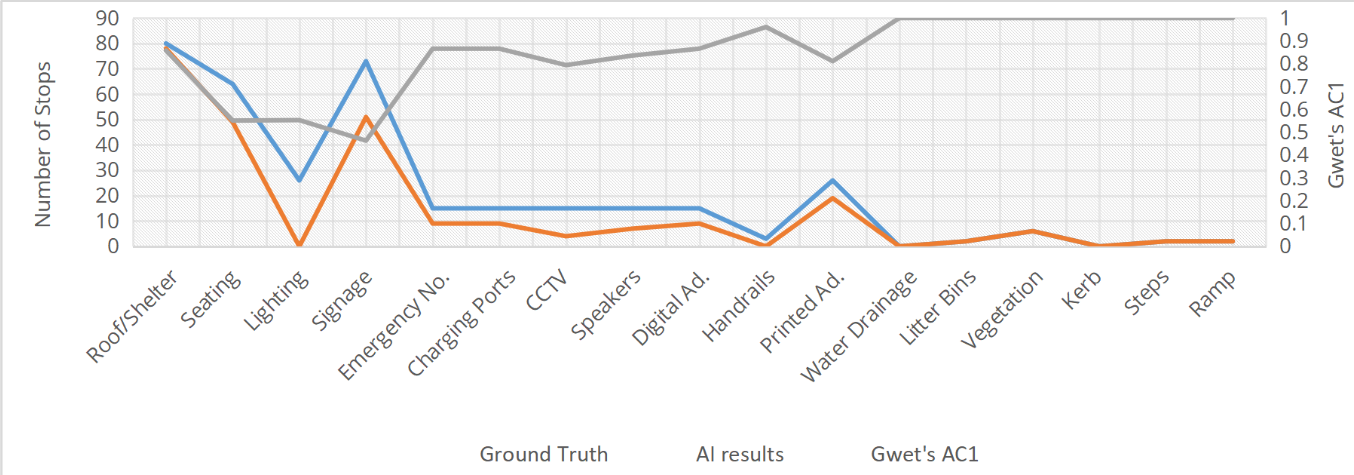

Figure 6. Per-class human–model agreement (Gwet's AC1), ranging from 0.551 to 1.0.

Figure 7. Infrastructural hierarchy identified in the study. Left: an old shelter on peripheral routes, lacking basic amenities. Centre: the only existing accessible stop in the dataset. Right: the latest type of bus stop infrastructure seen in the urban core, representative of the UNESCO programme.

survey was more efficient at 10.5 h, as travel was not required. The YOLOv8 model required a substantial upfront investment of 17.5 h, primarily for data annotation and model training; model performance is strongly influenced by the extent of this development, including annotation quality and local training. This highlights a fundamental difference in cost structure: traditional and digital surveys incur a recurring cost directly proportional to the number of stops, whereas the AI model incurs a one-time fixed cost that makes large-scale urban infrastructure analysis practically feasible.

The findings present a multi-layered critique of the public transport infrastructure in Thrissur, highlighting systemic issues of spatial equity, planning priorities, and regulatory enforcement. A development model that prioritises high-visibility central zones is evident from the strong spatial correlation between infrastructural quality and proximity to the urban core. The concentration of the largest UNESCO-programme stops around Swaraj Round—a high-density hub for both vehicle and pedestrian traffic—suggests a strategy focused on presenting the city's commercial and symbolic heart. This uneven development creates a de facto two-tiered transit system, in which a citizen's access to safe and comfortable facilities is determined by their location within the city.

This emphasis on visibility is compounded by the 'Modern but Inaccessible' paradox, a cautionary tale for 'smart city' development: modernisation strategies prioritise superficial, technological features—large digital advertising and charging ports—over deeper, functional aspects of a truly inclusive city. The real-world consequences are significant, as infrastructural deficits create de facto barriers to equitable access. A bus stop without ramps, handrails, or tactile markings is not merely non-compliant; it is effectively unusable for a differently abled citizen. Similarly, the lack of seating at smaller stops disadvantages passengers who cannot stand for long periods, and poor lighting raises legitimate safety concerns, particularly for women travelling at night. These are not mere flaws but active features of the built environment that can systematically exclude vulnerable segments of the population. Embedding universal design as a non-negotiable component is therefore a pressing need. The cost–benefit trade-off across the three methods is summarised in Table 7.

Table 7. Final pay-off between methods.

Method	Initial time cost	Survey 80 new stops	The "pay-off"
Traditional survey	25.3 h	≈25.3 h	Linear: scales 1:1; every new stop needs the same effort
Digital (GSV) survey	10.5 h	≈10.5 h	Linear: faster but still 1:1; limited by manual speed
AI (YOLOv8) method	17.5 h (one-time fixed)	≈15 s (inference)	Marginal cost per new stop is almost zero, enabling city-wide analysis

6 Conclusion

The following conclusions can be drawn from this study.

- A 'Modern but Inaccessible' paradox is evident: most stops (97.5%, i.e., 78 of 80) fail to comply with national standards (MoRTH and IRC). Provision is highly uneven (roofs 100%; ramps 2.5%; handrails 3.75%), and a de facto barrier reflects clear spatial inequality between the urban core and the periphery.
- The near-zero marginal cost after initial development (17.5 h one-time, versus approximately 15 s per inference), combined with the model's demonstrated detection performance, has a transformative impact on the scalability of urban infrastructure analysis.
- The model's F1, mAP, precision, and recall values indicate effective robustness.

Future work will explore the broader socio-spatial role of bus shelters in the urban fabric, including their relationship to safety and surveillance infrastructure; more comprehensive spatial mapping with higher-resolution imagery; and field-subset verification to address dimensional-analysis uncertainty using software such as ImageJ/Fiji.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

References

[1] Preston, J. (2020). Public transport. In *International Encyclopedia of Human Geography* (2nd ed., pp. 113-120). Elsevier. [CrossRef]

[2] *Cambridge Dictionary*. (n.d.). Retrieved April 12, 2026, from https://dictionary.cambridge.org/

[3] Kim, J., Park, J., Lee, J., & Jang, K. M. (2024). Examining the socio-spatial patterns of bus shelters with deep learning analysis of street-view images: A case study of 20 cities in the U.S. *Cities*, *148*, 104852. [CrossRef]

[4] Sijabat, K. R., Aufaristama, M., Wirawan Arief, M. C., & Dharmawan, I. A. (2025). Integrating remote sensing and street view imagery with deep learning for urban slum mapping: a case study from bandung city. *Applied Sciences*, *15*(14), 8044. [CrossRef]

[5] Ashok Leyland. (n.d.). *Viking VK2011.4T6R* [Brochure]. Retrieved April 15, 2026, from https://www.scribd.com/document/516120834/AL-BS-VI-Viking-Brochure-R6-13-04-2020

[6] Tata Motors. (n.d.). *Tata Starbus City* [Specifications]. Retrieved April 15, 2026, from https://busesandvans.tatamotors.com/brand/starbus

[7] Volvo Buses. (n.d.). *Volvo 8400 City Bus* [Brochure]. Retrieved April 15, 2026, from https://www.volvobuses.com/in/news/2010/vbus-launches-new-avatar-of-city-bus.html

[8] State Planning Board, Government of Kerala. (2017). *Economic Review 2017*. Retrieved April 15, 2026, from https://spb.kerala.gov.in/economic-review/ER2017/web_e/index.php

[9] Briant, S., Cushing, D., Washington, T., & Swart, M. (2025). Small but significant: a review of research on the potential of bus shelters as resilient infrastructure. *Applied Sciences*, *15*(12), 6724. [CrossRef]

[10] Ministry of Road Transport and Highways, Government of India. (2023). *Ministry of Road Transport and Highways*. Retrieved April 15, 2026, from https://morth.gov.in/

[11] Ministry of Road Transport and Highways. (2022). *Accessibility guidelines for bus terminals and bus stops*. Government of India. Retrieved April 15, 2026, from

https://a11y.enabled.in/accessibility-guidelines-for-bus-terminals-bus-stops-morth/

[12] Indian Roads Congress. (2015). *IRC 35: Code of practice for road markings* (revised). New Delhi: IRC. Retrieved April 15, 2026, from https://archive.org/details/gov.in.irc.035.2015

[13] Indian Roads Congress. (1981). *IRC 80: Type designs for pick-up bus stops on rural highways*. New Delhi: IRC. Retrieved April 15, 2026, from https://archive.org/details/govlawircy1981sp80_0

[14] Indian Roads Congress. (2018). *IRC SP 73: Manual of specifications and standards for two-laning of highways* (revised). New Delhi: IRC. Retrieved April 15, 2026, from https://archive.org/details/gov.in.irc.sp.073.2018/irc.gov.in.sp.073.2018/

[15] Indian Roads Congress. (2019). *IRC SP 84: Manual of specifications and standards for four-laning of highways* (updated). New Delhi: IRC. Retrieved April 15, 2026, from https://archive.org/details/gov.in.irc.sp.084.2019

[16] Indian Roads Congress. (2012). *IRC 103: Guidelines for pedestrian facilities*. New Delhi: IRC. Retrieved April 15, 2026, from https://law.resource.org/pub/in/bis/irc/irc.gov.in.078.2.2020.pdf

[17] Samsung. (n.d.). *Galaxy S22 Ultra-specifications*. Retrieved April 20, 2026, from https://www.samsungmobilepress.com/media-assets/galaxy-s22-ultra

[18] Roboflow. (n.d.). *Roboflow-Ultralytics integration*. Retrieved April 16, 2026, from https://docs.ultralytics.com/integrations/roboflow

[19] Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once: Unified, real-time object detection. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (pp. 779-788). [CrossRef]

[20] Jocher, G., Chaurasia, A., & Qiu, J. (2023). *Ultralytics YOLOv8*. Retrieved April 16, 2026, from https://docs.ultralytics.com/models/yolov8

[21] Padilla, R., Passos, W. L., Dias, T. L., Netto, S. L., & Da Silva, E. A. (2021). A comparative analysis of object detection metrics with a companion open-source toolkit. *Electronics, 10*(3), 279. [CrossRef]

[22] McHugh, M. L. (2012). Interrater reliability: The kappa statistic. *Biochemia Medica*, *22*(3), 276-282. [CrossRef]

[23] Gwet, K. L. (2008). Computing inter-rater reliability and its variance in the presence of high agreement. *British Journal of Mathematical and Statistical Psychology*, *61*(1), 29-48. [CrossRef]

[24] Wongpakaran, N., Wongpakaran, T., Wedding, D., & Gwet, K. L. (2013). A comparison of Cohen's kappa and Gwet's AC1 when calculating inter-rater reliability coefficients: A study conducted with personality disorder samples. *BMC Medical Research Methodology*, *13*(1), 61. [CrossRef]

[25] Schindelin, J., Arganda-Carreras, I., Frise, E., Kaynig, V., Longair, M., Pietzsch, T., ... & Cardona, A. (2012). Fiji: an open-source platform for biological-image analysis. *Nature methods, 9*(7), 676-682. [CrossRef]

[26] Mamidi, R. S., Kulkarni, B., & Singh, A. (2011). Secular trends in height in different states of India in relation to socioeconomic characteristics and dietary intakes. *Food and Nutrition Bulletin*, *32*(1), 23-34. [CrossRef]

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