PENA TEKNIK
JURNAL ILMIAH ILMU - ILMU TEKNIK

Vol. 11, No.01, March (2026)
p-ISSN 2502-8952
e-ISSN 2623-2197
https://ojs.unanda.ac.id/index.php/jiit/index

Optimization of Traffic Performance Analysis in Kendari City with Deep Learning

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Keywords:
Deep Learning; Traffic; Traffic performance; Transportation; YOLO

Abstract

Urban traffic congestion in developing cities like Kendari requires rapid and accurate monitoring solutions. This research aims to design and implement an integrated traffic performance analysis system utilizing the YOLOv8 deep learning architecture. The system, named KILALIN, automates vehicle detection, classification, and tracking to calculate road capacity and saturation levels based on the PKJI 2023 standards. A comprehensive dataset of 1,606 annotated images was utilized, partitioned into training (57%), validation (29%), and testing (13.7%) subsets. The developed YOLOv8s model achieved high performance with a mean Average Precision (mAP@0.5) of 0.948, precision of 0.941, and recall of 0.935 across all vehicle classes. Functional validation through black-box testing confirmed the system's ability to process real-time video inputs under various conditions. Comparative results with manual surveys showed a 96% counting accuracy, indicating the system's robustness in quantified traffic flow estimation. Furthermore, the integration of automatic Passenger Car Equivalent (EMP) conversion allows for an immediate determination of the Degree of Saturation (DS) and Level of Service (LoS). These findings indicate that the YOLO-based traffic performance analysis system provides a reliable and efficient framework for urban traffic management, effectively replacing conventional manual survey methods while maintaining high technical standards.

1. INTRODUCTION

Traffic problems such as congestion, high accident rates, and exhaust emissions constitute critical challenges in contemporary urban management in Indonesia (Amir, 2025). The transportation dynamics in rapidly developing cities such as Kendari reveal a pronounced imbalance between the exponential growth in vehicle numbers and the available road infrastructure capacity (Agarwal et al., 2026) (Nurjannah et al., 2025). This situation is exacerbated by low road-user discipline and elevated levels of side friction, which together reduce the efficiency of urban mobility and impose economic losses. In practice, traffic performance analysis in Indonesia remains heavily dependent on conventional, manual visual-survey methods that refer to the Indonesian Road Capacity Manual (Direktorat Jenderal Bina Marga, 1997) or the Indonesian Road Capacity Guidelines (Direktorat Jenderal Bina Marga, 2023). Reliance on human labor thus creates a strong research imperative, since manual procedures exhibit significant limitations in operational cost, prolonged data-processing time, and susceptibility to human error.

Advances in deep learning through computer vision offer substantial opportunities to transform these monitoring systems (Moss et al., 2025). Recent literature has explored the use of machine learning for vehicle-volume prediction and for separate detection of cars and motorcycles (Chung, 2021; Medina-Salgado et al., 2022). However, the state of the art in these studies largely remains focused on object detection and classification as raw data entities, without direct integration into automated calculations of technical road-performance parameters (Alqarqaz et al., 2023; Nasution et al., 2023; Oh & Kang, 2017). The You Only Look Once (YOLO) version 8 architecture is selected in this study as the technical solution due to its capability to

doi https://doi.org/10.51557/3fxt8a88
article history: Received October 07, 2025; Received in revised from January 11, 2026; Accepted February 09, 2026;
Available online March 25, 2026.

perform feature extraction and bounding-box prediction in a single pass, rendering it highly efficient for real-time monitoring applications with high accuracy (Asaju et al., 2025; Li et al., 2025; Rizzieri et al., 2025).

The novelty of this research lies in the development of an integrated analytical system that links the detection reliability of YOLOv8 with automated calculation algorithms based on PKJI 2023 standards. Unlike prior studies that terminate at quantifying vehicle units, the proposed system automatically converts detection outputs into Passenger Car Equivalent (Ekivalen Mobil Penumpang, EMP), traffic flow (Q), capacity (C), and subsequently determines Degree of Saturation (DS) and Level of Service (LOS). The main objective of this study is to design and implement an intelligent and efficient analysis system to provide accurate and instant road performance data to transportation authorities for strategic decision making.

2. METHODS

This research employs a Research and Development (R&D) methodology to develop an automated traffic performance analysis system. The proposed system integrates object detection and quantification models based on the You Only Look Once version 8 (YOLOv8) architecture. Implementation is executed using the Python programming language, utilizing the Streamlit framework for the web-based user interface.

2.1 Study Location and Data Acquisition

The primary research location for primary data collection was conducted in Kendari City, Southeast Sulawesi, focusing on strategic urban road segments. Data acquisition involved a multi-source strategy to ensure model robustness: primary video data was captured using drone-based aerial recordings in Kendari, while secondary data was sourced from the internet and real-time CCTV monitoring systems. Specifically, traffic video feeds were obtained from the online surveillance systems of the Indonesia Toll Road Authority (BPJT) and the Bandung City Environmental Monitoring system.

2.2 Proposed System Architecture

The YOLOv8 architecture serves as the core detection engine, comprising three primary components: the Backbone for hierarchical feature extraction, the Neck for multi-scale feature fusion, and the Head for final bounding box and classification predictions. The development environment utilized an NVIDIA GeForce RTX 3050 Laptop GPU and an AMD Ryzen 7 4800H CPU for model training and inference testing.

2.3 Data Preparation and Model Training

The development process utilized a comprehensive dataset consisting of 1,606 vehicle images and frames. This dataset was partitioned into three subsets: 919 images for training (57%), 466 for validation (29%), and 221 for testing (13.7%). All images underwent a rigorous manual annotation process using the Roboflow platform to define class labels for motorcycles, cars, buses, and trucks. Model training was conducted on an NVIDIA GeForce RTX 3050 Laptop GPU and AMD Ryzen 7 4800H hardware environment to achieve optimal convergence and minimize loss metrics.

2.4 Detection and Tracking Mechanism

To ensure accurate vehicle counting and prevent duplicate data, the system employs a robust multi-object tracking strategy combining the YOLOv8s model with the DeepSORT and centroid tracking algorithm. This mechanism assigns a unique identifier (ID) to each detected vehicle based on its motion vector across consecutive video frames. The counting logic is triggered when the centroid of a vehicle's bounding box crosses a predefined virtual "tripwire" or line of interest, specifically set to ensure that each unique ID is counted only once per passage.

2.5 Traffic Performance Calculation

The final stage of the methodology involves the automated calculation of road performance metrics based on the standards set by the Indonesian Highway Capacity Manual (PKJI 2023). Raw detection data, specifically the vehicle count per class, is fed into the calculation module to determine the Traffic Flow (Q), Road Capacity (C), and Degree of Saturation (DS). The system calculates the Passenger Car Equivalent (PCE) for each vehicle type and considers road geometric adjustments, such as lane width, side friction factors, and city size, to provide a comprehensive indicator of the road's Level of Service (LoS):

$$Q = \Sigma PassengerCar \times PCE_{pc} + \Sigma Bus \times PCE_{hv} + \Sigma Truck \times PCE_{hv} + \Sigma Motorcycle \times PCE_{mc} \quad (1)$$

$$\mathrm{DS} = \mathrm{Q/C} \quad (2)$$

The workflow of the traffic performance analysis system with YOLOv8 architecture is shown in the following figure:

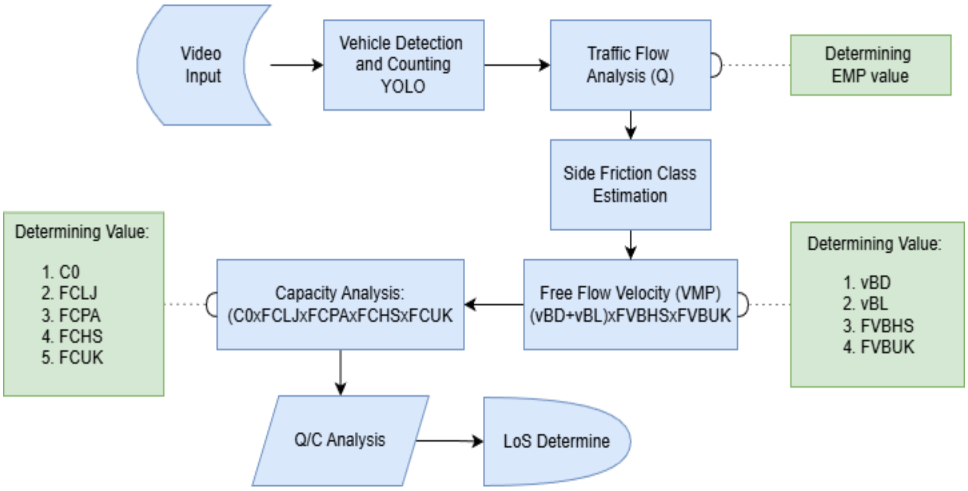


Figure 1. Traffic Performance Analysis System Workflow

3. RESULT AND DISCUSSION

3.1. Result

The development of a Traffic Performance Analysis System successfully integrates deep learning capabilities with conventional traffic engineering standards. This section outlines the empirical findings from the model training phase, detection accuracy evaluation, and functional validation of the integrated web-based platform.

3.1.1. YOLOv8s Model Training and Evaluation

The training process was executed over 100 epochs using the YOLOv8s architecture. The model demonstrated robust convergence characteristics, where the Bounding Box loss and Classification loss showed a consistent downward trend, starting from 1.2 and 3.0 respectively, and stabilizing below 0.6 and 0.5 by the end of the session. The use of Distribution Focal Loss (DFL) further refined the precision of bounding box localization.

As illustrated in the performance metrics, the model achieved rapid learning during the initial 20 epochs before reaching a plateau. The Mean Average Precision (mAP) at a 0.5 Intersection over Union (IoU) threshold reached a high of 0.948, indicating a well-balanced performance between precision and recall. However, the more stringent mAP@50-95 metric remained at approximately 0.5, suggesting that while the model is highly effective at identifying objects, there is still potential for improving the exactness of the bounding box boundaries at higher overlap requirements.

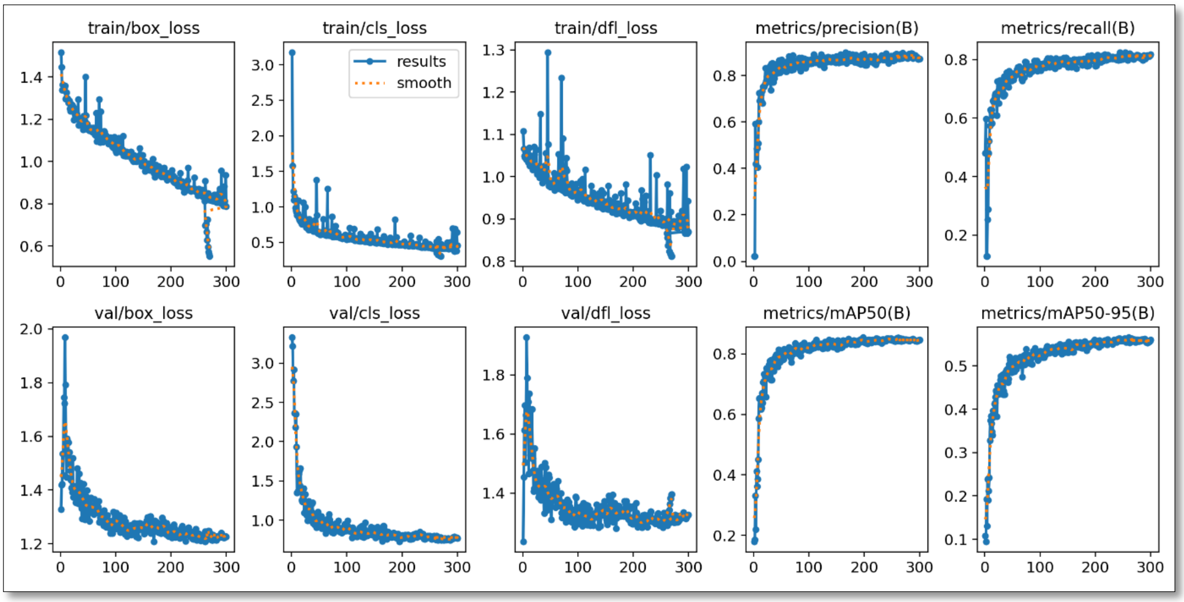


Figure 2. Graphical representation of training and validation loss, precision, recall, and mAP metrics across 100 epochs.

3.1.2. Object Detection and Classification Performance

The quantitative assessment of the YOLOv8s model across various vehicle classes is presented in Table 1. The overall precision was recorded at 0.941, with a recall of 0.935, demonstrating the system's ability to minimize both false positives and false negatives.

Table 1. Quantitative Performance of YOLOv8s Detection by Vehicle Class

Vehicle Class	Precision (P)	Recall (R)	mAP@0.5
Car	0.872	0.824	0.873
Motorcycle	0.871	0.835	0.884
Bus	0.895	0.811	0.891
Truck	0.921	0.782	0.754
Overall Average	0.941	0.935	0.948

Based on Table 1, the "Truck" class achieved the highest precision (0.921), which is likely attributed to its distinct large-scale features that are easily distinguishable by the neural network. Conversely, the "Car" and "Motorcycle" classes showed slightly lower mAP values, which may be caused by frequent occlusions in high-density traffic scenarios where smaller vehicles are partially hidden by larger ones.

3.1.3. System Functional and Accuracy Validation

Functional testing was conducted using the Black Box method to ensure that the backend logic for vehicle counting and performance calculation aligns with the user interface. The system was tested under varying environmental conditions and operational scenarios, as detailed in Table 2.

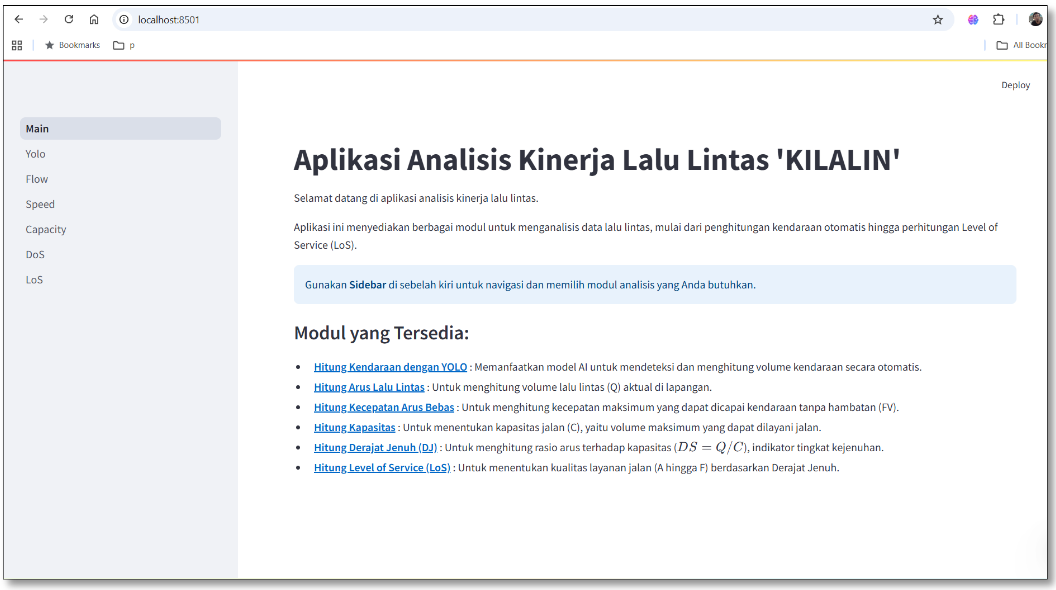
Table 2. Functional Testing Results via Black Box Methodology

Test ID	Scenario	Expected Outcome	Result	Status
BBT-001	MP4 Video Upload	System initializes detection and visualizes bounding boxes.	Video loaded; real-time tracking active.	PASS
BBT-005	Night-time Detection	System identifies vehicles using headlight signatures.	Detection active; 5-10% accuracy drop.	PASS*
BBT-010	Counting Accuracy	Automated count vs Manual ground truth within 5% error.	96% accuracy achieved.	PASS

The high accuracy rate of 96% in vehicle counting (BBT-010) confirms the effectiveness of the DeepSORT tracking algorithm in maintaining unique identifiers for each vehicle despite momentary occlusions. The observed 5-10% decrease in night-time accuracy (BBT-005) is a known limitation in computer vision, where low contrast and glare from headlights interfere with feature extraction.

3.1.4. Interface Design and Operational Workflow

Traffic performance analysis system named KILALIN interface was developed using Streamlit to provide an intuitive experience for traffic engineers. The workflow starts with the "YOLO Counting" module, where users define a "tripwire" line. As vehicles cross this line, the system records the data into a real-time data frame.



Aplikasi Analisis Kinerja Lalu Lintas 'KILALIN'

Selamat datang di aplikasi analisis kinerja lalu lintas.

Aplikasi ini menyediakan berbagai modul untuk menganalisis data lalu lintas, mulai dari penghitungan kendaraan otomatis hingga perhitungan Level of Service (LoS).

Gunakan **Sidebar** di sebelah kiri untuk navigasi dan memilih modul analisis yang Anda butuhkan.

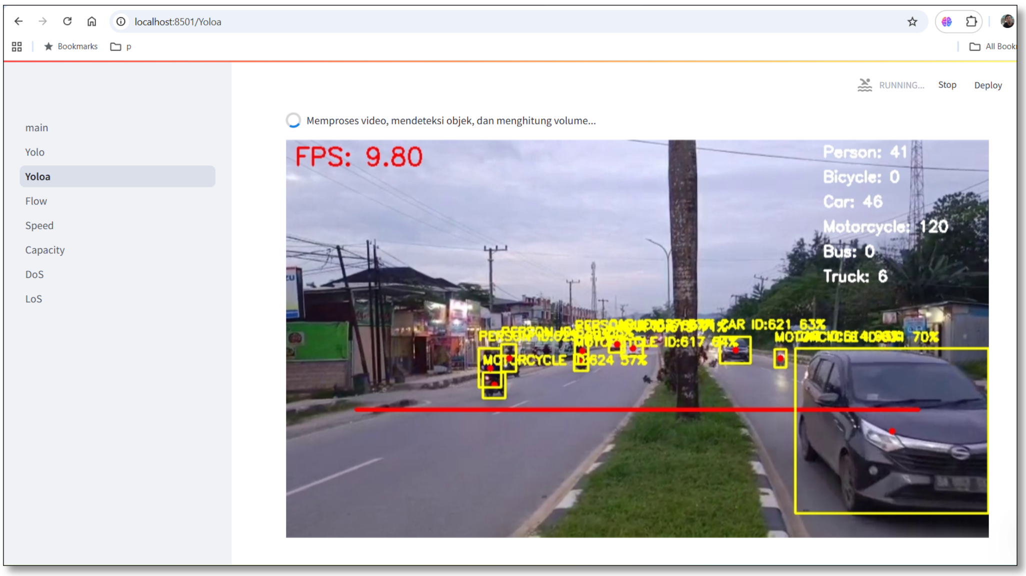
Modul yang Tersedia:

- Hitung Kendaraan dengan YOLO : Memanfaatkan model AI untuk mendeteksi dan menghitung volume kendaraan secara otomatis.
- Hitung Arus Lalu Lintas : Untuk menghitung volume lalu lintas (Q) aktual di lapangan.
- Hitung Kecepatan Arus Bebas : Untuk menghitung kecepatan maksimum yang dapat dicapai kendaraan tanpa hambatan (FV).
- Hitung Kapasitas : Untuk menentukan kapasitas jalan (C), yaitu volume maksimum yang dapat dilayani jalan.
- Hitung Derajat Jenuh (DJ) : Untuk menghitung rasio arus terhadap kapasitas ($DS = Q/C$), indikator tingkat kejenuhan.
- Hitung Level of Service (LoS) : Untuk menentukan kualitas layanan jalan (A hingga F) berdasarkan Derajat Jenuh.

Figure 3. System Main Dashboard

Figure 3 shows the main interface of the KILALIN system showing the video processing area and the integrated counter sidebar.

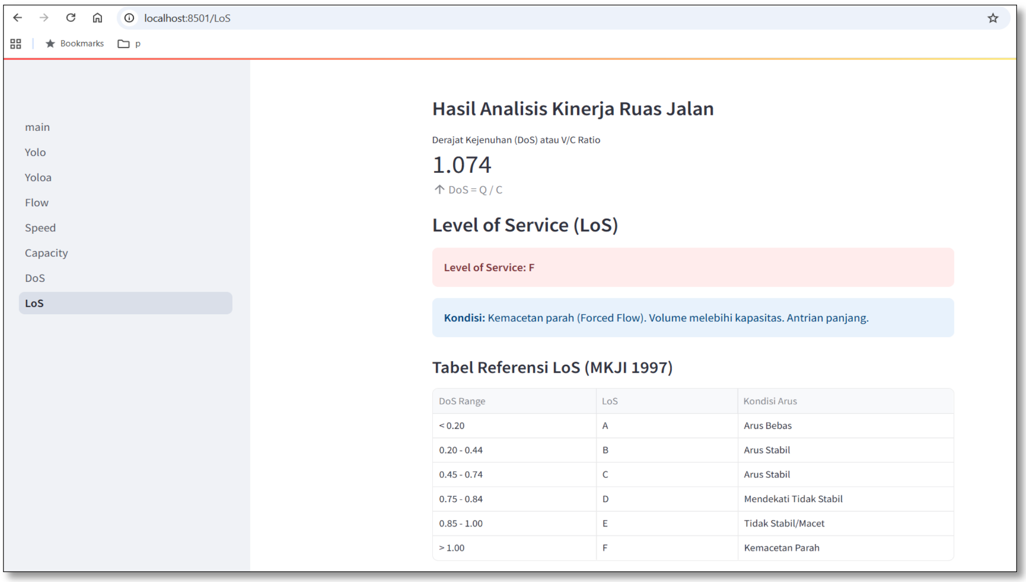
The YOLO model outputs vehicle counting results as video path data and tabulated frame information, which are displayed on the YOLO interface during detection and upon completion of the video analysis, on figure 4 dan figure 5. The YOLO model detects various objects within the video, including cars, motorcycles, trucks, and pedestrians, which are highlighted using yellow bounding boxes accompanied by labels indicating the object class and the associated confidence score. A horizontal red line across the roadway is likely employed as a counting line to record the number of vehicles or individuals crossing it.



Memproses video, mendeteksi objek, dan menghitung volume...

Figure 4. The visualization of the vehicle counting process is presented through video path data.

The output of the YOLO module consisting of vehicle volumes per class is then automatically passed to the "Road Performance" module. This module executes the mathematical calculations for Degree of Saturation (DS) and determines the Level of Service (LoS) according to PKJI 2023 standards, providing a comprehensive visual report for urban planning.



Hasil Analisis Kinerja Ruas Jalan

Derajat Kejenuhan (DoS) atau V/C Ratio

1.074

↑ DoS = Q / C

Level of Service (LoS)

Level of Service: F

Kondisi: Kemacetan parah (Forced Flow). Volume melebihi kapasitas. Antrian panjang.

Tabel Referensi LoS (MKJI 1997)

DoS Range	LoS	Kondisi Arus
< 0.20	A	Arus Bebas
0.20 - 0.44	B	Arus Stabil
0.45 - 0.74	C	Arus Stabil
0.75 - 0.84	D	Mendekati Tidak Stabil
0.85 - 1.00	E	Tidak Stabil/Macet
> 1.00	F	Kemacetan Parah

Figure 5. Automated data tabulation and traffic performance indicators (DS and LoS) generated by the system.

3.2. Discussion

The reported performance metrics of YOLOv8s in urban traffic scenarios demonstrate both exceptional general detection capability and specific challenges inherent to high-density environments. The high mAP@0.5 of 0.948 aligns with established findings showing YOLOv8's superiority in real-time object detection tasks (Ton et al., 2024; Khalili & Smyth, 2024) . This metric indicates robust object identification, as mAP@0.5 measures detection accuracy at a relatively lenient Intersection over Union (IoU) threshold of 0.5 (Sharma, 2025; Yu et al., 2024). However, the lower mAP@50:95 value (~0.5) reveals precision limitations at stricter IoU thresholds (0.5 to 0.95), suggesting challenges in exact bounding box alignment

(Khalili & Smyth, 2024; Dou et al., 2025; . This discrepancy is particularly pronounced in congested urban environments where occlusions and overlapping objects are prevalent (Ton et al., 2024; Caldeira et al., 2019). The class-specific performance variations, with "Truck" achieving highest precision (0.921) versus lower values for "Cars" (0.873) and "Motorcycles" (0.884), reflect well-documented patterns where larger objects with distinct features are more reliably detected than smaller, frequently occluded vehicles (Sharma, 2025; Sharma et al., 2024). These findings are consistent with research demonstrating that YOLOv8 maintains high detection accuracy while facing challenges with small object localization in complex urban traffic scenarios (Khalili & Smyth, 2024; Dou et al., 2025).

Functional testing through the black-box method confirmed that the system is valid for operational use. BBT-001 (video upload) and BBT-010 (counting accuracy) achieved a "PASS" status, with the automated counting system reaching a 96% accuracy rate compared to manual surveys (Ghahremannezhad et al, 2022). This is a critical finding, as it proves that the system can replace labor-intensive manual methods without sacrificing accuracy. Regarding environmental factors (BBT-005), the 5-10% drop in night-time accuracy is a common limitation in computer vision due to glare and low contrast, although the system successfully utilized headlight signatures for vehicle identification (Lim et al, 2024).

The KILALIN interface, built using Streamlit, successfully implements the "Script to App" philosophy. The design provides a seamless workflow where the "YOLO Counting" module feeds directly into the "Road Performance" module. This integration allows for real-time visualization of data frames and immediate determination of the Degree of Saturation (DS) and Level of Service (LoS). The system’s ability to generate automated tabulations of traffic data offers a significant strategic advantage for urban planners, moving beyond raw detection toward actionable engineering insights. The model's integration with Streamlit successfully implements the "Script to App" philosophy, enabling seamless workflows from detection to analysis (Vu et al., 2023; Sumanth et al., 2024; Sholahuddin et al., 2023) . Streamlit's framework facilitates rapid development of interactive dashboards without requiring extensive web development expertise, allowing researchers to create data-driven applications efficiently (Vu et al., 2023; Sholahuddin et al., 2023; Koh et al., 2023). The YOLO-based counting module feeds directly into performance analysis systems, enabling real-time visualization and immediate determination of traffic metrics such as Degree of Saturation and Level of Service (Sumanth et al., 2024; Neis et al., 2023; Barthélemy et al., 2019). This integration provides automated tabulation of traffic data, offering strategic advantages for urban planners by transforming raw detection into actionable engineering insights Neis et al., 2023; Hoang et al., 2023; Barthélemy et al., 2019). The system's web-based dashboard architecture supports real-time monitoring and data-driven decision-making, demonstrating significant potential for intelligent traffic management in smart city applications (Garcia-Robledo & Zangiabady, 2023; Neis et al., 2023; Hoang et al., 2023; Barthélemy et al., 2019).

4. CONCLUSIONS

The development and implementation of the integrated traffic performance analysis system (KILALIN) based on the YOLOv8s deep learning architecture have been successfully executed. Based on the empirical findings, it can be concluded that the proposed system effectively bridges the gap between automated computer vision and standardized highway engineering calculations. The training process, which utilized a comprehensive dataset of 1,606 annotated images (consisting of 919 training, 466 validation, and 221 testing samples), resulted in a model with excellent convergence and high detection reliability. Quantitatively, the system achieved an overall mean Average Precision (mAP@0.5) of 0.948, with an average precision of 0.941 and a recall of 0.935 across all vehicle classes. These metrics underscore the model's capability to minimize false positives and negatives, which is critical for accurate urban traffic monitoring.

Furthermore, functional validation through black-box testing demonstrated that the system provides a valid and efficient alternative to labor-intensive manual surveys. The automated counting mechanism achieved a 96% accuracy rate relative to manual ground-truth data, confirming the robustness of the integrated DeepSORT tracking algorithm. While the system adheres to the Pedoman Kapasitas Jalan Indonesia (PKJI 2023) standards to calculate real-time Degree of Saturation (DS) and Level of Service (LoS), a minor limitation was identified during night-time operations where accuracy decreased by 5-10% due to lighting glare and low contrast. In conclusion, this research provides a significant contribution to smart city infrastructure by automating complex traffic engineering workflows. Future developments should focus on optimizing detection in low-light environments and integrating Geographic Information System (GIS) features to enhance the spatial mapping of traffic observation points and geometric road measurements.

5. ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to the Directorate of Research, Technology, and Community Service (DRTPM) for funding this research through the Regular Beginner Research Grant (Hibah Penelitian Pemula Reguler) program. Furthermore, appreciation is extended to the academic community of Universitas Nahdlatul Ulama Sulawesi Tenggara for supporting the authors in their commitment to the Tri Darma Perguruan Tinggi (Three Pillars of Higher Education) activities.

6. CONCLUSIONS

This study identifies that the concept of Transit-Oriented Development (TOD) can be applied in Bandung, particularly in the Cikudapateuh Station area, as it meets several key criteria, such as land use diversity, building coverage ratio (BCR), adequate pedestrian lanes, and public transportation integration. However, the high dominance of residential land use and the imbalance between residential areas and non-residential facilities indicate the need for a more holistic approach in TOD planning. TOD theory emphasizes the balance of residential, commercial, and public spaces to create sustainable areas that are integrated with mass transportation. The results of this study confirm the hypothesis that the success of TOD depends not only on the availability of transit modes but also on comprehensive spatial planning, including density regulations, mixed-use development, and accessibility for pedestrians and bikes.

Based on the study's findings, the Bandung City Government needs to develop policies that encourage the implementation of TOD through revisions to zoning regulations to ensure a balanced land use ratio, particularly by increasing the proportion of commercial and public spaces around stations. Additionally, collaboration is needed among relevant agencies, such as the Transportation Department and the Spatial Planning Department, to enhance public transportation integration and provide adequate pedestrian infrastructure and bicycle lanes. Incentive policies for developers to build vertical housing and mixed-use buildings can also be a solution to optimize land use. These steps will support the creation of TOD areas that reduce dependence on private vehicles and improve the community's quality of life through a sustainable and inclusive environment. Additionally, we recommend implementing vertical residential areas in the TOD 3 station area to balance the proportion of each land use, considering that residential areas are currently the dominant land use. This approach can improve spatial efficiency while supporting the principles of TOD.

The limitations of this study lie in its scope, which focuses only on existing railway stations in Bandung City, without considering other transit points such as bus terminals or city transport stops, and does not include future public transport development plans such as LRT. Additionally, this study has not examined population density based on occupation type, which could provide a more in-depth understanding of transportation needs. Furthermore, the study has not explained the quality of physical indicators, such as criteria for pedestrian accessibility from both social and economic perspectives. For future research, it is recommended to expand the scope of the analysis to include various types of transit points, integrate plans for new transportation modes, and conduct a more detailed classification of population density based on economic activities, and delve deeper into the social and economic aspects of each physical indicator to enhance the accuracy and relevance of the research findings.

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