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YOLO-Based Real-Time Artificial Intelligence Traffic Counting for Urban Transportation Monitoring in Surakarta: Implications for SDG 11

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ABSTRACT

Objective: *To develop and evaluate an artificial intelligence (AI)-based traffic counting system using the YOLO (You Only Look Once) deep learning algorithm to provide accurate and real-time traffic volume data for urban transportation management.* ***Method:*** *Employing a deep learning approach by implementing the YOLO algorithm for vehicle detection and traffic counting. Traffic video data from road objects in Surakarta City were processed to identify and classify various vehicle types. The AI-generated traffic counting results were then compared with manual traffic survey data to assess the system's accuracy and effectiveness.* ***Results:*** *The findings indicate that the proposed AI-based traffic counting system can accurately detect and classify multiple vehicle categories, including cars, motorcycles, trucks, buses, bicycles, and Bajaj. The traffic-counting data produced by the system were highly readable and reliable. Comparison with manual traffic surveys showed that the AI-generated results were very similar while requiring significantly less time and human resources. The system achieved nearly 100% consistency with the available secondary traffic volume data, demonstrating its effectiveness in monitoring urban traffic conditions.* ***Novelty:*** *Application of the YOLO deep learning algorithm for automated traffic counting in the urban road environment of Surakarta City. The proposed system provides a practical and efficient alternative to conventional manual traffic surveys by delivering accurate, real-time traffic data with minimal human intervention, thereby supporting more effective urban transportation planning and management. These contributions are also relevant to SDG 11 (Sustainable Cities and Communities) by enabling data-driven traffic monitoring and facilitating smarter, more sustainable urban mobility management.*

INTRODUCTION

The problem of transportation, especially land transportation in Indonesia, is quite complex because transportation is an interrelated system. If a problem arises in a single unit or network, it will affect the system as a whole (Hendratmoko & Dewantoro, 2018). Traffic delays, accidents, and increased pollution are often the outcome of complex traffic problems that most urban regions face (Leroux et al., 2022). Transportation agencies are increasingly concerned about the high number of traffic fatalities and their recent rise, which makes research into intersection user safety crucial. A considerable amount of crash data is typically required to develop safety assessment analyses. Preparing crash data is subject to several limitations, including challenging data-collection procedures, lengthy data-collection periods, and underreporting (Patel et al., 2023).

One potential answer is using real-time data to build more dynamic routes and manage traffic. By maintaining continuous traffic flow and directing cars away from impediments, a system that employs variable message signs, for instance, can reduce motor vehicle emissions and traffic bottlenecks (Unzilatirrizqi et al., 2019; Chatterjee & McDonald, 2004). Access to transportation-related data is critical to mitigating traffic accidents. This information includes facility usage, vehicle data, and traffic volume (Unzilatirrizqi et al., 2019). However, these methods depend on precise traffic statistics (Leroux et al., 2022). Traffic data is gathered, traffic characteristics are identified, vehicle composition is ascertained, and traffic performance is measured through traffic counting or enumeration of the quantity and kind of vehicles (Oltean et al., 2019). The results of traffic counts can also be utilized to control the movement of passengers and products (Pratama et al., 2021). There are two main methods used for traffic counting: mechanical counting and manual counting (with stationery) (Pratama et al., 2021; Khraisat et al., 2019). It is recognized that this activity still exhibits relatively large errors and gaps in the accuracy of the calculations and results.

These challenges are closely related to Sustainable Development Goal 11 (SDG 11), which emphasizes the importance of developing inclusive, safe, resilient, and sustainable cities. Reliable and timely traffic information is essential for supporting evidence-based transportation policies, reducing congestion, improving mobility efficiency, and strengthening smart city initiatives. Therefore, innovative approaches to traffic monitoring are increasingly needed to facilitate sustainable urban transportation management.

In this study, we suggest using cameras to measure how often automobiles, bicycles, and pedestrians travel in a specific direction. Our streets and cities are already replete with surveillance cameras. Recent advancements in computer vision technology enable it to produce highly accurate counting results (Leroux et al., 2022; Unzilatirrizqi et al., 2019). Traffic flow prediction (TFP) is increasingly using artificial intelligence (AI) to improve prediction accuracy (Chen et al., 2023). As a crucial area of computer science, artificial intelligence (AI) has drawn much attention from scholars. When learning the traits concealed in massive amounts of data, artificial intelligence (AI) can combine a variety of cutting-edge theories and technologies to finish related decision-making tasks (Jiang et al., 2020).

Artificial intelligence, or AI for short, is one of the advances in information technology. The technology known as artificial intelligence enables robots, computer systems, software, and programs to think like people (Khraisat et al., 2019). The significance of computer vision applications for in-car navigation, video surveillance, computer-human interaction, and autonomous vehicle development has increased due to advancements in object-tracking technologies (Soleimanitaleb & Keyvanrad, 2019). In various applications, such as object classification, artificial intelligence (AI), and machine learning (ML), these technologies have become indispensable (Liu & An, 2020; Ngeni et al., 2024). However, these methods depend on precise traffic statistics. In this work, we propose counting how often cars, bikes, and pedestrians move in a given direction using cameras. Our streets and cities are already replete with surveillance cameras. They can now deliver highly accurate counting results thanks to recent advancements in computer vision technology. The primary advantage of vision-based methods is that they provide fine-grained categorization, enabling us to distinguish among various motorized vehicle types, cyclists, and pedestrians (Leroux et al., 2022).

Target tracking algorithms and motion recognition have made it simple to track a car's speed (Dong et al., 2021). Thanks to these developments in intelligent transportation systems (ITS), vehicles can now be detected, alerted, counted, and classified under different circumstances (Kamkar & Safabakhsh, 2016). By extracting information from the relevant time-spatial image, such as vehicle length, and computing correlations or associations from the co-occurrence matrix of the vehicle image with a bounding box, these technologies enable the counting and classification of vehicles (Ngeni et al., 2024). This study provides precise vehicle detection when a vehicle crosses a boundary or as needed. To achieve very precise data, including counts, city names, street names, and the desired counting direction, the feed source you wish to detect or count can be an IP camera or video feed. It is also possible to automatically save the counting results into a Microsoft Excel report file.

RESEARCH METHOD

Currently, numerous studies and apps have investigated traffic congestion (Carvalho Barbosa et al., 2020). You provide state-of-the-art object identification performance with Only Look Once (YOLO) algorithms. This study proposes a novel, one-stage YOLO-based method that explicitly models the spatial context of traffic locations. To successfully leverage extensive global contextual information, the new YOLO*C algorithm improves the loss function and adds the MCTX context module (Oreski, 2023). The process of identifying the class to which an object belongs and estimating its location by generating a bounding box around it is known as object detection. Transportation is one of the many fields in which object detection is used (Oreski, 2023; Pathak et al., 2018). Transport networks are essential to much of civilization's economy since they transfer people and goods. These transportation networks regularly experience traffic congestion, reducing their usefulness and needlessly raising air pollution and fuel consumption. Due to highly volatile mobility demand, proposals to alleviate traffic congestion must be developed and implemented swiftly—and often in near real time. However, their effectiveness is hindered by the costly and rapidly obsolete traffic survey data (Gan et al., 2021).

Many real-time image identification systems have investigated various deep learning algorithms; however, solutions based on the SSD and YOLO architectures have achieved the best performance in the current literature (Redmon, 2018). A traffic light detection system utilizing SSD was demonstrated, and the response time yielded good results with high accuracy (Gu et al., 2017; Müller & Dietmayer, 2018). Similarly, using YOLO resulted in higher processing speeds and highly accurate object detection, as documented in the literature (Zhang & Zhu, 2019). However, it is necessary to enhance current models to further reduce processing time without sacrificing accuracy in the context of traffic signals, where numerous images must be analyzed in real time (Carvalho Barbosa et al., 2020). The current study proposes the Priority Vehicle Image Detection Network (PVIDNet), an enhanced version of YOLOV8.

YOLO uses a unified, fast object detection method (Redmon, 2018). The main reason is that YOLO is fast enough for real-time object detection, a massive advantage when coupled with a live video feed, as it opens up the potential for real-time systems (Gan et al., 2021). It has been found that YOLO computes more quickly than any other model and achieves the best recall, accuracy, and precision (Liu et al., 2020). Its processing is simple with a mean Average Precision (mAP) of 63.4% and real-time image processing at 45 frames per second (FPS). Yolo uses the ImageNet-1000 dataset and the Darknet framework to train the model. YOLO is, nevertheless, limited by how close the objects are to one another in the picture (Adarsh et al., 2020). Another drawback concerns object proportions; if these deviate from those in the training-phase photos, the model detects positional errors that interfere with object detection (Jiao et al., 2019; Zhao et al., 2019).

The backbone (the feature extractor network), neck, and head are the three main parts of the YOLO architecture. A deep convolutional neural network is the main component, extracting features from the input image. Multiple layers of convolution and pooling that gradually downsample the input image make up the backbone of most systems. The backbone is designed to extract high-level elements useful for image object identification. Several backbones are used by the YOLO family of object detection algorithms to extract features from the input image. CSPDarkNet-53, CSPNet, DarkNet-19, and DarkNet-53 are a few of them (Chen et al., 2023).

RESULTS AND DISCUSSION

Results

AI-Based traffic counting system development

The needs analysis phase of this program starts with identifying the necessary software and its needs. To identify algorithmic actions, including reading video files, extracting information, initializing variables and functions, and processing data, flow planning and program execution methods are then performed. At this phase, other features are also found to enhance the program's functionality. Vehicle photos from a high-quality dataset that has undergone extensive testing and verification are used in this paper. A new dataset was created to train and test the suggested method because it took time to locate an existing dataset that included photographs of various vehicle types with comparable image attributes. This dataset includes a variety of automobile domains for the Indonesian city of Surakarta. The next step is preparing the dataset, which entails gathering and selecting traffic video datasets based on the software's requirements. There are two categories of datasets: training and validation. Annotated information on the items to be detected is included in the training dataset see in Figure 1.

(a) (b)

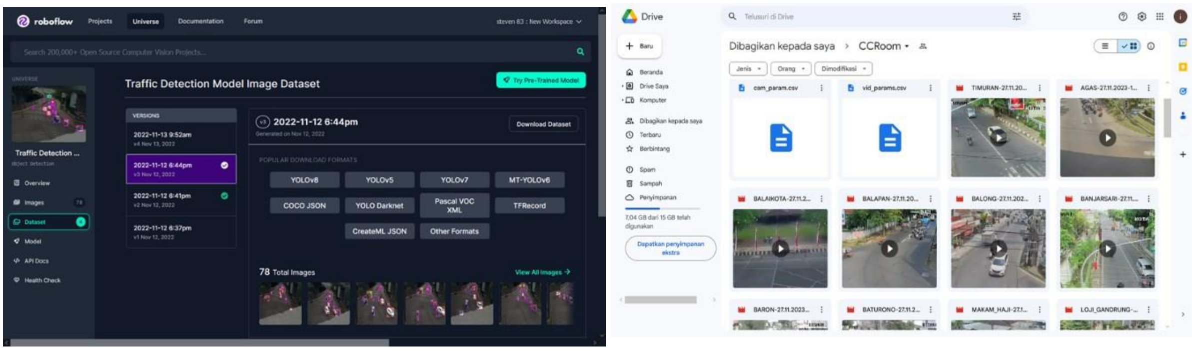
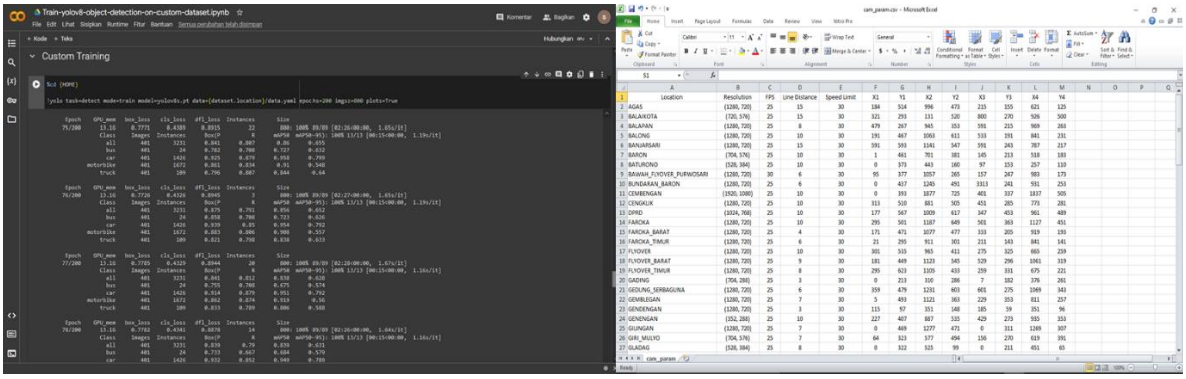


Figure 1. (a) Traffic detection model; (b) dataset preparation

This dataset comes from the Roboflow traffic-detection-model-wsoka and contains 78 images across five categories: auto, car, truck, motorcycle, and bus. The YOLO models are trained in this phase using the YOLOv8 framework. To meet specific requirements, models are trained on annotated datasets with customized training parameters, including learning rate, batch size, and number of epochs. The purpose of this procedure is to improve the system's object detection capability. After completing 78 epochs, the training process produced a YOLO model weighing 22,103 KB.

An algorithm is a representation of the steps involved in object detection. The variables are initially introduced along with the program. The next step is to determine the camera parameters, with details provided for each linked camera. These include the camera location, line-drawing points (X1–Y4), the distance between two lines measured in meters, and a speed limit parameter of 30 km/h, see in Figure 2.



(a) (b)

Figure 2. (a) Training YOLO model; (b) determination of camera parameters

The system architecture consists of a backbone, neck, and head module. The backbone extracts image features, the neck aggregates features, and the head performs object detection. Program performance is validated by comparing detection outcomes with expected results to ensure that the system functions properly in Figure 3.

Figure 3. Testing and validation

Following testing, optimization procedures are implemented to improve detection speed and analytical performance. The source code is written in Python and utilizes FFmpeg, Supervision, and Ultralytics libraries for object detection, analysis, and data storage. Additional functionalities include hash computation, detection data processing, video compression, and integration with Google Drive and Google Colab for efficient storage and execution.

Discussion

Real AI traffic counting implementation

The developed system was implemented using secondary CCTV data obtained from the Surakarta City Communications Service. The traffic footage was processed using the Artificial Intelligence Traffic Counting (AITC) system for 10 minutes. A total of 89 observation points were analyzed using both conventional traffic counting data and AITC-generated results. The system successfully detected several vehicle categories, including bicycles, cars, trucks, buses, and other vehicle types. Vehicle movement was analyzed by direction, namely, bottom-to-top and top-to-bottom, within the video frame in Figure 4.

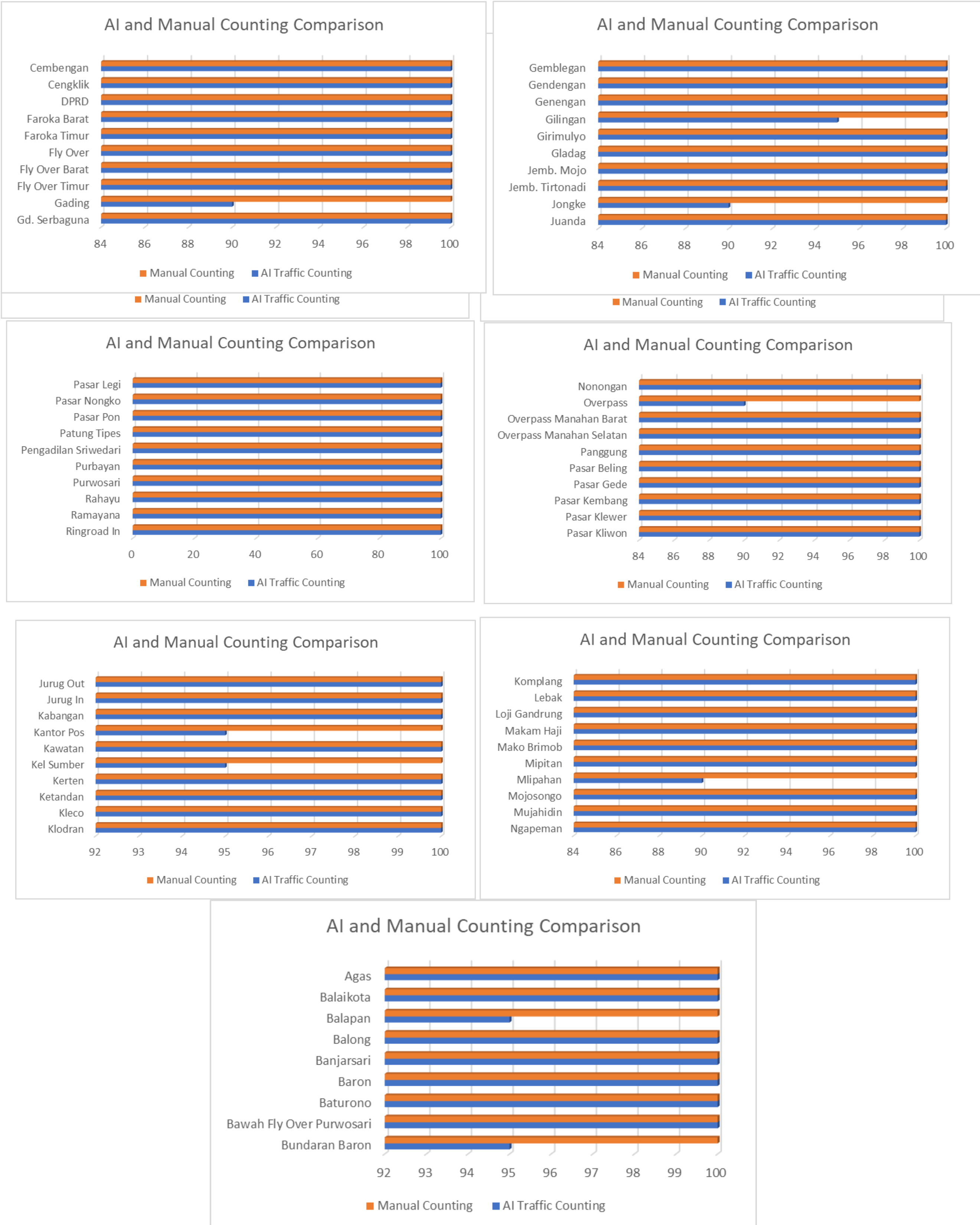


Figure 4. AI and manual counting comparison

The results demonstrate that AI-based traffic counting can effectively detect, classify, and count moving vehicles automatically without direct human intervention. The implementation confirms that AI-based traffic monitoring provides highly accurate traffic information while reducing the time and labor required for manual surveys. This finding supports the growing adoption of computer vision and artificial intelligence technologies in transportation systems, particularly in urban areas where large volumes of traffic data must be collected continuously. Although challenges remain due to weather conditions, lighting variations, vehicle occlusions, and differences in vehicle appearance, the majority of detections were successfully recorded without missing objects. The comparison between AI-generated traffic counts and conventional traffic data indicates a very high level of agreement. Most observation locations showed approximately 100% correspondence between AI results and secondary traffic volume data, while only a small number of locations showed approximately 95% agreement. These results indicate that the proposed system can maintain high detection accuracy under real-world traffic conditions.

The high correspondence between AI-generated and manually collected traffic data demonstrates the robustness of the YOLO-based detection framework. The ability to automatically identify multiple vehicle categories while maintaining detection accuracy suggests that the system can be effectively applied to urban traffic monitoring activities. Furthermore, the system can continuously process video streams, making it more suitable for long-term traffic observation than traditional survey methods, which are often constrained by human resources, observation duration, and operational costs.

Compared with conventional traffic counting approaches, the proposed AI-based system offers several advantages. First, the automated process significantly reduces the need for human involvement during data collection and processing. Manual traffic surveys typically require multiple surveyors to observe and record vehicle movements, increasing both labor costs and the possibility of human error. In contrast, the AI-based system automatically detects and counts vehicles, resulting in greater efficiency and consistency. Second, the system enables near real-time monitoring, allowing transportation agencies to obtain traffic information immediately after data acquisition. Such capabilities are particularly valuable for congestion monitoring, traffic signal optimization, and incident management.

Another important finding is the system's ability to classify vehicles into different categories. Vehicle classification is essential for transportation planning because different vehicle types contribute differently to traffic flow characteristics, road capacity utilization, pavement deterioration, fuel consumption, and environmental impacts. The ability to distinguish between motorcycles, cars, buses, trucks, and bicycles allows transportation planners to obtain more detailed traffic information and develop targeted transportation policies.

The implementation results also demonstrate the scalability of the proposed system. Since the input source can originate from existing CCTV infrastructure, transportation agencies do not necessarily need to install additional hardware to conduct traffic monitoring. This reduces implementation costs and facilitates wider deployment across urban road networks. The integration with cloud-based platforms such as Google Drive and Google Colab further enhances accessibility by enabling centralized data storage, remote processing, and simplified system maintenance.

Despite the promising results, several limitations should be acknowledged. Environmental factors such as heavy rain, poor illumination at night, shadows, and temporary obstructions may affect detection performance. Similarly, dense traffic situations can lead to vehicle overlap and occlusion, potentially affecting counting accuracy. Future improvements may include incorporating more diverse training datasets, employing advanced tracking algorithms, and utilizing additional camera viewpoints to reduce detection uncertainty under complex traffic conditions.

From a practical perspective, the findings indicate that AI-based traffic counting can serve as an effective alternative to conventional traffic surveys. The technology provides rapid, reliable, and repeatable traffic measurements while minimizing operational costs. As urban populations grow and transportation networks become increasingly complex, the demand for accurate, real-time traffic information will continue to rise. Therefore, AI-based traffic monitoring systems have significant potential to support smart city initiatives, intelligent transportation systems (ITS), traffic management centers, and data-driven transportation planning.

These findings also underscore the relevance of this study to SDG 11 (Sustainable Cities and Communities). The availability of accurate, real-time traffic information can support evidence-based transportation decision-making, improve the efficiency of urban mobility, and strengthen smart city initiatives. By reducing reliance on labor-intensive manual surveys and enabling continuous traffic monitoring through existing infrastructure, AI-based traffic counting systems may contribute to the development of more sustainable, resilient, and data-driven urban transportation systems.

CONCLUSION

Fundamental Finding: This study demonstrates that the YOLO (You Only Look Once) deep learning algorithm can be effectively applied to real-time traffic counting using CCTV footage in Surakarta City. The proposed AI Traffic Counting (AITC) system successfully detected and counted various vehicle types with high accuracy. The results showed a strong agreement between AI-generated traffic counts and secondary traffic volume data, with most locations achieving nearly 100% correspondence. Moreover, the AI-based approach produced results comparable to manual traffic surveys while requiring less time and human resources. **Implication**: The findings indicate that AI-based traffic counting can serve as an efficient and reliable alternative to conventional traffic survey methods. The system supports real-time traffic monitoring and can assist transportation agencies in traffic management, congestion analysis, and transportation planning. These implications are aligned with SDG 11 (Sustainable Cities and Communities), highlighting the potential of AI-driven traffic monitoring to support smarter mobility management, evidence-based transportation policies, and more sustainable urban transportation systems. **Limitation**: This study was limited to CCTV data from selected locations in Surakarta City and may be affected by factors such as lighting conditions, weather variations, and vehicle occlusion that can influence detection performance. **Future Research**: Future studies should evaluate the proposed system using larger and more diverse datasets from different cities and traffic environments. Additional research may also integrate vehicle speed estimation, traffic density analysis, and predictive traffic management features to improve system functionality.

AUTHOR CONTRIBUTIONS

Bambang Istiyanto contributed to the conceptualization of the study, research design, project supervision, validation of research findings, and critical review of the manuscript. **Yan El Rizal Unzilatirrizqi D** contributed to software development, data collection, implementation of the artificial intelligence traffic counting system, data analysis, visualization, and drafting of the manuscript. **Alfan Baharuddin** contributed to methodology development, interpretation of results, data validation, and manuscript revision. **Pipit Rusmandani** contributed to literature review, data processing, administrative support, and manuscript editing.

CONFLICT OF INTEREST STATEMENT

The authors affirm that there are no financial, personal, or professional conflicts of interest that may have influenced the conduct, findings, or conclusions of this research.

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The authors declare that no AI-based tools, automated content generators, or digital writing assistants were employed during the research, analysis, or writing of this manuscript. All research activities, including data analysis, result interpretation, and manuscript preparation, were performed independently by the authors. The authors are fully accountable for the originality, reliability, and integrity of the content reported in this study.

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