Jurnal Teknik Informatika (JUTIF)
Vol. 5, No. 4, August 2024, pp. 253-261
DOI: https://doi.org/10.52436/1.jutif.2024.5.4.2063
p-ISSN: 2723-3863
e-ISSN: 2723-3871

TRAFFIC FLOW AND CONGESTION DETECTION WITH YOLOV8 AND BYTETRACK-BASED MULTI OBJECT TRACKING

Marchel Maulana Fahrezi*[1], Eka Angga Laksana[2]

[1,2]Faculty of Engineering, Universitas Widyatama, Indonesia
Email: [1]marchel.fahrezi@widyatama.ac.id, [2]eka.angga@widyatama.ac.id

(Article received: May 8, 2024; Revision: May 18, 2024; published: August 01, 2024)

Abstract

The rapid urbanization witnessed in cities like Bandung, Indonesia, has emerged as a pressing issue, precipitating severe traffic congestion that poses challenges to economic growth and diminishes overall quality of life. This study endeavors to confront these multifaceted challenges through the development of a sophisticated real-time traffic surveillance and control system. The proposed system utilizes the current CCTV infrastructure in the city and incorporates advanced technologies like YOLOv8 for accurate vehicle detection and ByteTrack for dynamic real-time vehicle tracking. This system utilizes a comprehensive strategy, including multi-object tracking techniques to improve the precision of congestion detection. The system was thoroughly assessed in several places in Bandung, and it showed remarkable performance metrics. Specifically, YOLOv8 achieved an impressive 80% accuracy rate in vehicle detection, showcasing its efficacy in discerning vehicles within complex urban environments. Simultaneously, ByteTrack exhibited an average error rate of 17% in vehicle counting, further Strengthening the system's capabilities in accurately quantifying vehicular traffic. Furthermore, the combination of YOLOv8 and ByteTrack in a multi-object tracking paradigm yielded an 80% accuracy rate in congestion detection, emphasizing the system's robustness in real-time traffic management scenarios. These findings underscore the immense potential of the integrated YOLOv8 and ByteTrack system in traffic management strategies and alleviating congestion in smart cities like Bandung. This research has produced precise outcomes in identifying and quantifying the traffic congestion in various scenarios.

Keywords: *ByteTrack, Congestion Estimation, Traffic Counter, Vehicle Detection, YOLOv8.*

1. INTRODUCTION

The exponential growth of urban populations, coupled with advancements in technology, has given rise to the concept of smart cities as a means to address the complex challenges of modern urban living. Smart cities leverage human capital and cutting-edge infrastructure to foster sustainable economic development and enhance overall quality of life [1]. Boyd Cohen's seminal work on smart cities delineates a comprehensive approach aimed at optimizing city operations, improving residents' well-being, and stimulating local economic activities. Key components of smart cities encompass Smart Mobility, Smart People, Smart Living, Smart Government, Smart Environment, and Smart Economy[2].

However, rapid urbanization often leads to congestion and inefficiencies in transportation systems, which can hamper economic growth and diminish residents' quality of life [3]. For example in Bandung City exemplifies these challenges, with a burgeoning vehicle population nearly on par with its human inhabitants. By 2023, vehicle numbers soared to 2.2 million, while the population stood at 2.4 million, as reported by the Bandung City Transportation Office. This influx of vehicles, coupled with non-compliance with traffic regulations and underutilization of public transport, exacerbates congestion, particularly during peak hours. The resultant economic toll, quantified at 4 trillion rupiah, underscores the urgent need for innovative solutions in urban transport management [4], [5].

The integration of imagery and scientific methodologies presents a highly effective approach applicable to various domains, including transport management and offer insights into traffic dynamics, vehicle types, speed profiles, and behavioral patterns[6]. This intersection allows for a deeper understanding of key aspects such as vehicle counts, types, speeds, and movement behaviors[7]. Initially, cameras are strategically positioned to capture surveillance videos of roadways or tracks, which are then subjected to computerized image processing and computer vision algorithms. Techniques such as object detection and motion analysis contribute to measuring vehicle speeds to a certain extent[8], enabling the development of sophisticated traffic tracking systems[9].

A leading method in this field of Deep Learning is YOLO (You Only Look Once), which is well-known for its effectiveness in tasks such as object detection, including counting people or recognizing objects within images [10], [11]. YOLO's distinct "end-to-end" methodology streamlines object detection into a single step, unlike traditional multi-stage processes [12]. In traffic management, YOLO proves useful for tasks like vehicle counting and traffic violation identification, often integrated with OCR (Optical Character Recognition) technology, as evidenced by experiments in India[13]. YOLO currently at its 8th version, YOLOv8, prioritizing accuracy-speed balance and offering a range of pre-trained models for diverse application needs [14].

Despite its strengths, YOLO lacks contextual comprehension and object tracking capabilities, necessitating supplementary Multi Object Tracking methods. ByteTrack, recognized as the leading Multi Object Tracking method, employs a novel approach of associating items based on their tracklet similarity, allowing for chronological context construction and efficient object movement monitoring [15].

In previous studies, YOLOv8 has shown promising results as a state-of-the-art deep learning model for object detection and classification, demonstrating its potential for real-time applications[16], [17]. Another research conducted by Anggraini et al. [18] investigated the application of YOLO, a deep learning method, for social distancing detection. Their research aimed to find the optimal camera angle for a system that could accurately measure the distance between people show impressive result with Mean Average Precision 90%. Recent research conducted by Abouelyazid, M [19] has highlighted the superior performance of ByteTrack compared to other established tracking algorithms like SORT and DeepSORT. Its innovative one-shot detection-based approach has proven to be a game-changer, particularly in complex scenarios like highway timelapse videos, where it consistently delivers higher accuracy, fewer identity switches, and faster processing speeds. This makes ByteTrack a promising solution for real-time tracking applications in traffic monitoring.

The need for effective traffic management solutions in rapidly growing urban areas like Bandung has motivated this research. Building upon recent advancements in deep learning and object tracking, and inspired by promising results in previous studies, this study aims to harness the capabilities of YOLOv8 and ByteTrack to develop a real-time traffic flow and congestion detection system. The integration of YOLOv8's object detection prowess with ByteTrack robust tracking capabilities is expected to enable more accurate and efficient identification, classification, and tracking of vehicles within traffic surveillance footage. This research seeks to contribute to the field of smart city traffic management by providing a novel framework for real-time traffic monitoring and control, with the potential to improve congestion mitigation strategies and optimize urban mobility.

2. METHOD

2.1. Algorithm Design

Multi object tracking - which is able to use computer vision as well as object detection and tracking technology - can be applied to identify and monitor different types of moving objects, for example, vehicles on the road [20]. Such tracking of the objects through speed and the direction of movements provides the needed information for the estimation of the time taken by the samples from their source of origin. Thus, it allows for control of the movement of vehicles and discovery of any pinch points. In this study, the monitoring region is subdivided into three detection zones that can be seen in Figure 1, namely, the entry zone used to mark the time and speed of passing vehicles, count zone used to measure the waiting time as well as the travel time taken by vehicles, and finally the exit zone which is the area for data-capture considered to be used for the time and speed of leaving the monitoring region. The information generated by aforementioned three-hole patching reveals the basic analytical data concerning traffic flow, which further to detect specific patterns that inevitably create traffic jams. With the counter zone, researchers can evaluate traffic conditions immediately without having to wait for vehicles to exit the exit zone.

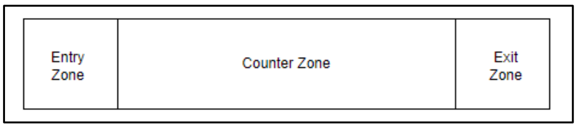

Figure 1. Image Detection Zone

The system workflow, illustrated in Figure 2, begins by feeding captured input data into the YOLOv8 classification model. This model analyses the input data to detect objects within the image. Once objects are identified, the ByteTrack process is initiated to track their movement across consecutive video frames, providing a seamless examination of the detected objects. Finally, the system examines the patterns of the identified and tracked objects.

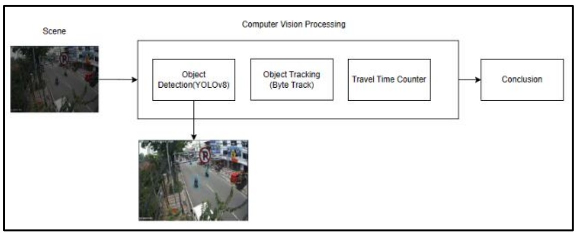

Figure 1. Proposed System Pipeline

Moreover, the determination of traffic congestion can be made by calculating the average trip time in the observed area, using the following formula:

$$\bar{T} = \frac{1}{n}\sum_{i=1}^{n} T_i \quad (1)$$

Where $\bar{T}$ represents the average travel time in the observed area, n is the total number of trips taken during the observation period, T_i represents the time taken for each individual trip, indexed from 1 to n. The formula (1) is essential for evaluating the effectiveness and efficacy of transportation networks. A lower mean trip duration typically signifies more efficient traffic flow and improved accessibility, whereas a larger mean may indicate congestion or delays within the area. The accuracy of the traffic condition detection and vehicle count calculation is based on the following equation:

$$Acc = \frac{Predicted}{Actual}\, x\, 100\% \qquad (2)$$

The error rate is also obtained by performing the following equation:

$$Error = 100\% - Acc \qquad (3)$$

The formula (2) and formula (3) are used to assess the performance of traffic condition detection and vehicle flow count calculation systems. Formula (2), which calculates accuracy as the ratio of predicted values to actual values multiplied by 100%, quantifies the degree to which the system's predictions align with the ground truth. On the other hand, formula (3), representing the error rate, highlights the proportion of incorrect predictions made by the system, offering a complementary perspective on its performance.

2.2. Tools and Materials

The tool used in this research is a Lenovo V14 laptop and uses a dedicated server using an NVIDIA Tesla P4 GPU to run the modelling and implementation of the system that has been developed. The material used in this research comes from CCTV in Bandung. Detail explanation about the dataset will be explain in Data Understanding Phase.

2.3. Research Flow

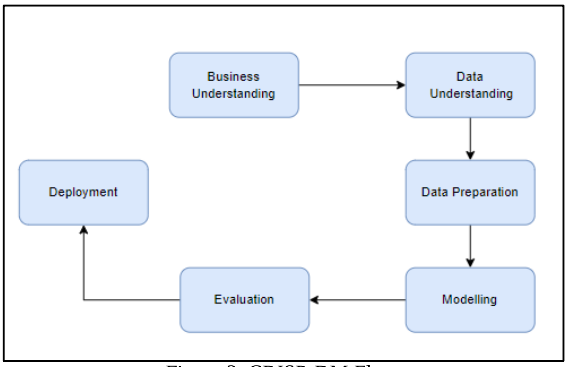

Figure 3. CRISP-DM Flow

This research uses the CRISP-DM reference model, which provides a systematic framework for the entire research process, from business understanding to system implementation that can be seen in Figure 3. Its flexibility allows adaptation to different projects and environments, focusing on model development, deep business understanding, and comprehensive performance evaluation.

2.4. Business Understanding Phase

This phase is the initial phase of CRISP-DM. This phase requires understanding by starting to determine the research topic, identifying the problem that needs to be solved, and setting the goals to be achieved. The next phase involves collecting data through literature studies on previous research relevant to this topic. Next, system design is conducted, including the selection of algorithms and research parameters.

2.5. Data Understanding Phase

This phase is the phase to collect data and understand the data that will be used in the research. The purpose of this phase is to recognize the data to be used and try to make an initial identification of data quality. In this research, the data is obtained from capturing CCTV of Bandung city which can be accessed publicly and online. The data is captured in several times, in 18 October 2023, 19 October 2023, and 24 February 2024 with the total amount of data that has been collected has a resolution of 640x480 with 0.3 MP which amounts to 1183 images taken in different time spans and conditions to be used as material for testing the accuracy level of the system to be built.

2.6. Data Preparation Phase

During this phase, the dataset is prepared until it reaches its final form. The actions involved in this phase include preprocessing, labeling, and dividing the dataset into training and testing sets, which will be used as input for the system. Preprocessing is a crucial step in data processing that enhances the quality and durability of the analysis. The data obtained from CCTV footage of Bandung city will now undergo a variety of modifications. Some typical steps in preprocessing include. Normalization ensures that the data is standardized to have a consistent scale, preventing any attribute from overpowering others. In addition, the process of assigning labels to pre-processed picture data is conducted in order to identify the specific classes that will be classed. This study specifically focuses on the Motorcycle and Car classes.

The purpose of this separation is to train the model on the training dataset and test its performance on the test dataset, so that it can be evaluated to what extent the model can generalize the learned patterns. Before performing the modelling phase, image transformation is required such as changing the image orientation, and resizing the image size so that all images have the same size and image orientation.

Figure 4. Image Contrast Adjustments

In image orientation adjustment preprocessing, a transformation process is performed that aims to correct the orientation or position of the image to conform to the standard. This include rotation, alignment, distortion, or cropping of the image to improve visual quality and consistency before modelling. The image size adjustment stage aims to ensure that all images in the dataset have uniform and standard dimensions. The next preprocessing stage is contrasting enhancement based on the image histogram to improve normalization and line detection under varying lighting conditions. Figure 4 show example of image contrast adjustments.

2.7. Modelling Phase

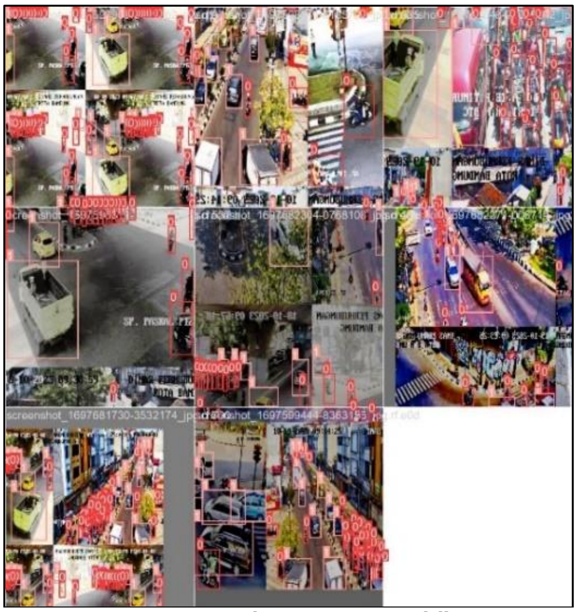
Figure 5. YOLO Object Detection Modelling

Datasets that have been labelled and separated into training and test as show in Figure 5, the next step is to train using the YOLOv8 algorithm. In the modelling stage, YOLOv8 will be instructed to learn patterns and characteristics from the training dataset.

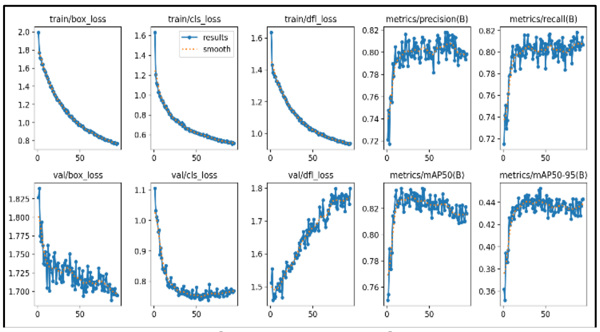

Figure 6. YOLO Object Detection Evaluation Matrix

During the training process, the model will adjust its weights and biases in order to optimize its performance, as measured by the loss function, with the goal of achieving a high level of accuracy. The image modelling findings indicate that the mAP (Mean Average Precision) for validation is consistently high and remains stable throughout the training cycles. On the whole, the model demonstrated a mean accuracy of 80% at every iteration, as illustrated in Figure 6.

2.8. Evaluation Phase

After the completion of the modeling process, the subsequent phase involves assessing the precision of the model. The assessment can be conducted by utilizing a test dataset that has been previously segregated. The evaluation findings offer insights into the model's ability to accurately identify objects in unfamiliar data. Subsequently, the proficient model will be kept for utilization in the deployment phase. Frequently, the evaluation stage must be tailored to meet unique requirements, necessitating a repetition back to the modeling phase until data preparation is complete. System evaluation, in addition to model evaluation, encompasses several parameters to assess the appropriateness of the conditions in the implemented system.

1) System testing will be carried out at various time conditions, namely morning, afternoon, and evening.
2) System testing will be carried out at several accessible CCTV camera points in Bandung.
3) The test will include the condition of the vehicle when it is quiet and has a lot of objects in it.

Testing is carried out using a sample frame because it ensures that the output results of the conditions inferred by the system match the real conditions at the time of testing.

2.9. Deployment Phase

During this phase, the system will be implemented by recording data through CCTV cameras deployed in multiple sites throughout the city of Bandung. The recording data comprises visual picture recordings that will subsequently serve as input for the system.

3. RESULTS

In this study, traffic conditions at various locations in Bandung City were tested and the number of vehicles traveling on the observed roads was counted, example of implementations can be seen in Figure 8. The testing of traffic conditions will be divided into three categories, namely smooth, slow-moving, and congested, to evaluate the level of density and smoothness of traffic flow in the area. A smooth condition is when a vehicle can cover the distance in less than 5 seconds, the traffic flow moves smoothly without significant obstacles. A slow-moving condition occurs when the vehicle takes between 5 to 10 seconds, causing a decrease in speed. Congested conditions are when vehicles take more than 10 seconds to cover the same distance. This condition indicates that the traffic flow is experiencing high congestion, resulting in very slow and stalled vehicle movements.

3.1. Traffic Flow Count Testing

The vehicle enumeration test was carried out by systematically examining the flow of traffic at a certain place and documenting the total count of cars that traversed the region during a specified timeframe. Furthermore, this test is undertaken to assess the efficacy of YOLOv8 and ByteTrack in detecting vehicle objects at different locations. Based on the data shown in Table 1, it can be inferred that there is a discrepancy between the predicted values and the actual values. At the Antapani site, the projected vehicle count is 304, whereas the observed count is 320. Similar incidents occurred at the Asia Afrika BRITower, Burangrang, Cikutra, and Dipatiukur Unikom sites. This difference can be attributed to multiple variables, one of which being a suboptimal camera position.

Table 1. Summary of traffic flow results

Location	Prediction	Actual
Antapani	304	320
Asia Afrika BRITower	337	380
Burangrang	107	139
Cikutra	102	155
Dipatiukur Unikom	90	102

When the camera position is not correct, there is overlap between vehicles, so detection models such as YOLO v8 cannot accurately recognize the actual number of vehicles. Figure 7. illustrates that there is an average error of 17% in the calculation of the number of vehicles from several locations.

The lowest error rate occurs in the Antapani area with a percentage of 5%, while the highest error rate reaches 34%. This indicates that there is significant variation in the accuracy of vehicle count predictions across locations, where some locations may be more difficult to predict correctly than others.

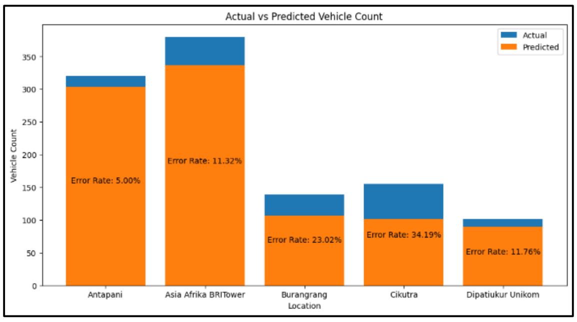

Figure 7. Comparison of traffic flow result in each location

Figure 8. Image and object tracking example

3.2. Traffic Condition Detection Testing

The traffic condition identification test was carried out by monitoring several traffic scenarios at pre-determined places. The purpose of this test is to assess the system's capacity to identify and categorize traffic situations, such as smooth, slow-moving, or congested, using visual data captured by the camera. This testing procedure entails comparing the system's detection outcomes with the manually seen or recorded actual conditions. The test results will yield data regarding the accuracy rate of detection, the rate of errors, and potential factors that influence the performance of the traffic detecting system.

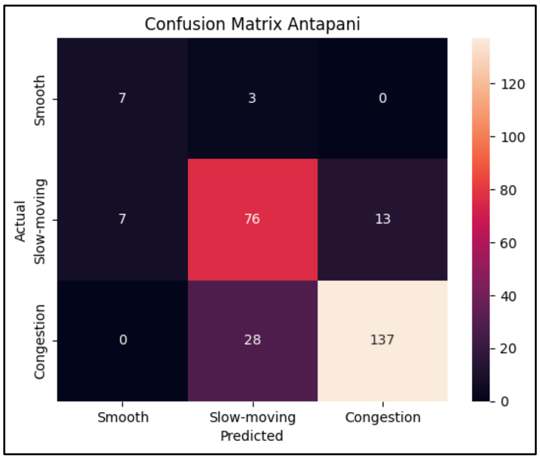

Figure 9. Detection result of Antapani area

According to Figure 9, the detection of traffic conditions in the Antapani area was carried out effectively with an accuracy rate of 80.29%, while the percentage of unsuccessful detections was 19.71%. This demonstrates that the traffic condition recognition system at that specific site has a commendable degree of precision in identifying and categorizing traffic situations, such as flowing smoothly, moving slowly, or experiencing congestion, by analyzing the visual data it captures. According to Figure 10, it was found that the average time taken to travel in the calculation zone located in the Antapani area was in the range of over five seconds.

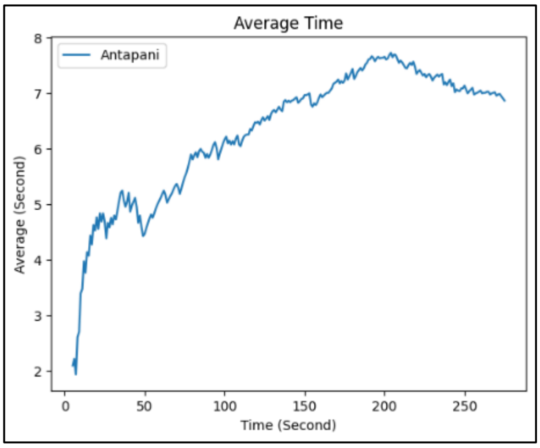

Figure 10. Average travel time in the count zone

This information is based on image data collected in the afternoon, with a total image capture time of 4.28 minutes. Unlike the information contained in Figure 9 for the Antapani area which shows an accuracy rate of about 80.29%, Figure 11 shows different results for the Cikutra area.

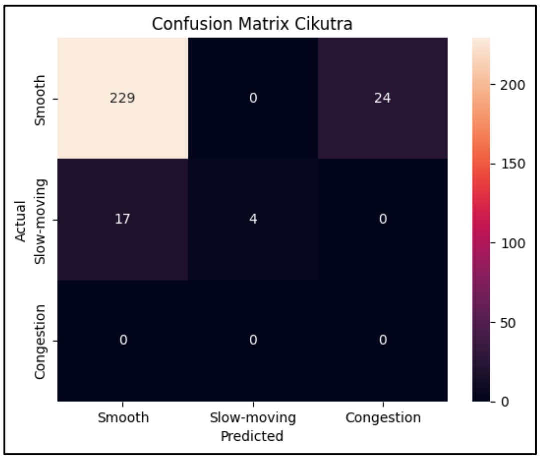

Figure 11. Detection result of Cikutra area

The traffic condition detection results show a success rate of 85.04%, with a failure rate of 14.96%. It is important to note that this test was conducted in the afternoon, which suggests that there may be variations in accuracy depending on the time of day the data was collected and the geographical location. Figure 12 clearly demonstrates a substantial disparity in travel time in comparison to Figure 10. The recorded average travel time falls within a range of around 2 seconds. The disparity can be ascribed to the geographical conditions in the observed region. The existence of slopes along the route may lead to vehicles moving at a reduced speed, which is expected to impact the total travel duration. Furthermore, the existence of a junction after the hill could also contribute as an additional factor.

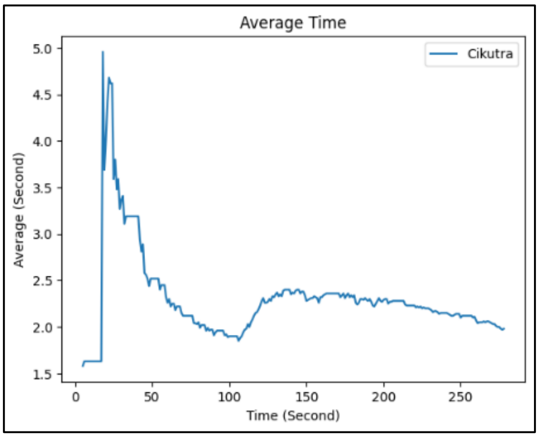

Figure 12. Average travel time in the Cikutra area

Table 2 indicates that the accuracy levels differ for each site. The Asia Africa BRITower and Dipatiukur Unikom sites demonstrated a perfect accuracy rate of 100%, with few or nonexistent detection errors.

Table 2 Summary of detection results at each location

Location	Accuracy	Error
Antapani	80,29%	19,71%
Asia Afrika BRITower	100%	0%
Burangrang	94,53%	5,47%
Cikutra	85,04%	14,96%
Dipatiukur Unikom	100%	0%

The Antapani site has an accuracy rate of 80.29% and a detection error rate of 19.71%. The Burangrang site has an accuracy rating of 94.53% and a detection error rate of 5.47%. However, the Cikutra site has an accuracy rate of 85.04% and a detection error rate of 14.96%. The sample of test data can be seen in Table 3.

Table 3 Samples of detection results at each location

Location	Seconds to	Prediction	Actual
Antapani	60	Congested	Congested
Asia Afrika BRITower	200	Smooth	Smooth
Burangrang	150	Smooth	Smooth
Cikutra	18	Congested	Smooth
Dipatiukur Unikom	100	Smooth	Smooth

The variation in the precision of the congestion detection system at the specified locations in the data can be attributed to several factors, such as disparities in the camera arrangement and the resolution of the cameras employed in the system. First and foremost, variations in camera arrangement can impact the detection of cars. If the cameras are not positioned appropriately or lack enough viewing angles, it can result in vehicles overlapping with each other. Consequently, certain cars may be inadequately detected or not detected at all. Furthermore, the level of detecting accuracy might be influenced by the camera resolution. Cameras with low resolution may lack the ability to generate images that are clear and highly detailed, resulting in reduced accuracy in detecting vehicles. On the other hand, high-resolution cameras have the ability to capture images with more clarity and finer details, resulting in enhanced accuracy in detecting objects.

4. DISCUSSION

The results obtained from the traffic flow count testing and traffic condition detection testing provide valuable insights into the performance and limitations of the integrated YOLOv8 and ByteTrack system in traffic management scenarios. These findings prompt several discussions regarding the accuracy, error rates, and factors influencing the performance of the detection system. The training process for YOLOv8 Object Detection show the Mean Average Precision (mAP) for validation remains consistently high and stable throughout training. The model demonstrates a mean accuracy of 80% across iterations. The Integration of YOLOv8 and ByteTrack show the accuracy of the system for varied between 80.29% and 100%, with corresponding error rates ranging from 0% to 19.71%. Locations like Asia Africa BRITower and Dipatiukur Unikom exhibited perfect accuracy, while Antapani and Cikutra had lower accuracy rates. This variance reflects the impact of geographical factors, camera placement, and environmental conditions on detection precision. Geographical factors, including camera positioning and resolution, significantly influenced accuracy. Inaccurate camera placement and low-resolution cameras led to overlaps and reduced accuracy. Environmental conditions such as slopes and traffic densities also affected accuracy, with complex traffic patterns posing challenges. Testing at different times of the day showed varying accuracy rates, particularly in congested traffic conditions. For instance, the Antapani area exhibited lower accuracy during congestion. Additionally, high-resolution cameras with optimal viewing angles enhanced detection accuracy by providing clearer images and reducing detection errors from overlapping visual data.

In prior research, Manurung, et al [21] employed computer vision technology, specifically YOLOv4, to detect vehicles in traffic videos. While they achieved decent accuracy on traffic congestion detection. Their study also reported an average object detection accuracy of 61.3% on their specific dataset. Our current study, employing a different dataset but leveraging the advancements in YOLOv8, observed an improved average object detection accuracy of 80%. This suggests that YOLOv8's advancements have the potential to contribute to more accurate object detection in traffic scenarios. Jie Ng, et al [22] developed a Traffic Impact Assessment System using YOLOv5 and ByteTrack to address heavy traffic issues in Malaysia. Their comprehensive system included vehicle detection, counting, classification, idling time analysis, and junction-based counting. While their study demonstrated the effectiveness of combining YOLO and ByteTrack, they primarily focused on traffic impact assessment, whereas our research emphasizes real-time traffic flow and congestion detection. Their comparison of ByteTrack with other tracking methods, such as StrongSORT and OC-SORT, underscores the importance of choosing an appropriate tracking method based on the specific application. The findings of this research, when compared with these previous studies, indicate that the integration of YOLOv8 and ByteTrack holds promise for improving the accuracy and real-time capabilities of traffic management systems in smart cities. However, it is crucial to acknowledge the limitations of this study, such as the need for further refinement in handling complex traffic scenarios and optimizing camera placement and resolution for varying environmental conditions.

5. CONCLUSIONS

This study has demonstrated the potential of integrating YOLOv8 and ByteTrack for real-time traffic flow and congestion detection in urban environments. The results indicate that the YOLOv8 model achieved an average precision of 80% in object detection, while the combined YOLOv8 and ByteTrack system achieved an accuracy of 83% in traffic flow counting and 80% in congestion detection. These findings highlight the effectiveness of this integrated approach in accurately identifying and tracking vehicles, even in varying traffic conditions.

However, it is important to acknowledge that the system's performance is influenced by several factors, including camera placement, environmental conditions, and traffic density. These factors can introduce variability in accuracy rates across different locations and times of day. Therefore, future research should focus on optimizing camera setup, refining the algorithms to handle complex traffic scenarios, and investigating the impact of environmental variables on system performance.

Overall, this study can contribute valuable insights to the field of smart city traffic management, demonstrating the potential of YOLOv8 and ByteTrack to enhance traffic monitoring and control systems.

ACKNOWLEDGEMENTS

The authors would like to acknowledge contributions of the Mr. Frans Agus Budiharto, CEO of PT Semesta Teknologi Informatika for the invaluable support provided during the conduct of this work.

LITERATURE

[1] V. Rosalina, Y. Sugiyani, and A. Triayudi, “PERANCANGAN INFRASTRUKTUR JARINGAN KOMPUTER DALAM KONSEP MEMBANGUN SERANG MENUJU SMART CITY,” *Jurnal PROSISKO*, vol. 1, 2014.

[2] A. S. Harahap and P. Zulvia, “Analisis Pengembangan Smart City berdasarkan Dimensi Teknologi, Sumber Daya Manusia, dan Insitutional di Kota Padang Panjang,” *Media Online)*, vol. 4, no. 1, pp. 618–624, 2023, doi: 10.30865/klik.v4i1.1200.

[3] F. A. Nuzir, “Smart People, Smart Mobility. Konsep Kota Pintar yang Bertumpu pada Masyarakat dan Pergerakannya di Kota Metro”, doi: 10.13140/RG.2.1.3056.4324.

[4] M. A. Asset and S. Sugiyanto, “ANALISA BIAYA KERUGIAN KARENA MENGALAMI KONDISI KEMACETAN AKIBAT PERBAIKAN JALAN DITINJAU DARI WAKTU TUNDA PERJALANAN DAN KENAIKAN BAHAN BAKAR MINYAK (BBM) KENDARAAN,” *Rang Teknik Journal*, vol. 4, no. 1, pp. 143–163, Jan. 2021, doi: 10.31869/rtj.v4i1.2268.

[5] R. Akhmad Hermawan and R. Haryatiningsih, “Dampak Kemacetan di Kota Bandung bagi Pengguna Jalan,” *Bandung Conference Series: Economics Studies*, vol. 2, no. 1, Jan. 2022, doi: 10.29313/bcses.v2i1.680.

[6] V. Zinchenko, G. Kondratenko, I. Sidenko, and Y. Kondratenko, “Computer Vision in Control and Optimization of Road Traffic,” in *2020 IEEE Third International Conference on Data Stream Mining & Processing (DSMP)*, 2020, pp. 249–254. doi: 10.1109/DSMP47368.2020.9204329.

[7] C. Shiranthika, P. Premaratne, Z. Zheng, and B. Halloran, “Realtime computer vision-based accurate vehicle counting and speed estimation for highways,” in *Intelligent Computing Theories and Application: 15th International Conference, ICIC 2019, Nanchang, China, August 3–6, 2019, Proceedings, Part I 15*, 2019, pp. 583–592.

[8] H. Mejia, E. Palomo, E. López-Rubio, I. Pineda, and R. Fonseca, “Vehicle speed estimation using computer vision and evolutionary camera calibration,” in *NeurIPS 2021 Workshop LatinX in AI*, 2021. doi: 10.52591/202112072.

[9] B. Qi, W. Zhao, H. Zhang, Z. Jin, X. Wang, and T. Runge, “Automated traffic volume analytics at road intersections using computer vision techniques,” in *2019 5th International Conference on Transportation Information and Safety (ICTIS)*, 2019, pp. 161–169.

[10] L. Rahma, H. Syaputra, A. H. Mirza, and S. D. Purnamasari, “Objek Deteksi Makanan Khas Palembang Menggunakan Algoritma YOLO (You Only Look Once),” 2021.

[11] T. A. A. H. Kusuma, K. Usman, and S. Saidah, “PEOPLE COUNTING FOR PUBLIC TRANSPORTATIONS USING YOU ONLY LOOK ONCE METHOD,” *Jurnal Teknik Informatika (Jutif)*, vol. 2, no. 1, pp. 57–66, Feb. 2021, doi: 10.20884/1.jutif.2021.2.2.77.

[12] R. Al-batat, A. Angelopoulou, S. Premkumar, J. Hemanth, and E. Kapetanios, “An End-to-End Automated License Plate Recognition System Using YOLO Based Vehicle and License Plate Detection with Vehicle Classification,” *Sensors*, vol. 22, no. 23, Dec. 2022, doi: 10.3390/s22239477.

[13] A. Tonge, S. Chandak, R. Khiste, U. Khan, and L. A. Bewoor, “Traffic Rules Violation Detection using Deep Learning,” in *2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, 2020, pp. 1250–1257. doi: 10.1109/ICECA49313.2020.9297495.

[14] G. Jocher, A. Chaurasia, and J. Qiu, “Ultralytics YOLOv8.” 2023. [Online]. Available: https://github.com/ultralytics/ultralytics

[15] P. and J. Y. and Y. D. and W. F. and Y. Z. and L. P. and L. W. and W. X. Zhang Yifu and Sun, “ByteTrack: Multi-object Tracking by Associating Every Detection Box,” in *Computer Vision – ECCV 2022*, G. and C. M. and F. G. M. and H. T. Avidan Shai and Brostow, Ed., Cham: Springer Nature Switzerland, 2022, pp. 1–21. doi: 10.1007/978-3-031-20047-2_1.

[16] E. Soylu and T. Soylu, “A performance comparison of YOLOv8 models for traffic sign detection in the Robotaxi-full scale autonomous vehicle competition,” *Multimed Tools Appl*, vol. 83, no. 8, pp. 25005–25035, 2024, doi: 10.1007/s11042-023-16451-1.

[17] F. M. Talaat and H. ZainEldin, “An improved fire detection approach based on YOLO-v8 for smart cities,” *Neural Comput Appl*, vol. 35, no. 28, pp. 20939–20954, 2023, doi: 10.1007/s00521-023-08809-1.

[18] M. D. Anggraini, K. Kusrini, and H. Al Fatta, “SOCIAL DISTANCING DETECTION FINDING OPTIMAL ANGLE WITH YOLO V3 DEEP LEARNING METHOD,” *Jurnal Teknik Informatika (Jutif)*, vol. 3, no. 5, pp. 1449–1455, Oct. 2022, doi: 10.20884/1.jutif.2022.3.5.390.

[19] M. Abouelyazid, “Comparative Evaluation of

SORT, DeepSORT, and ByteTrack for Multiple Object Tracking in Highway Videos," *International Journal of Sustainable Infrastructure for Cities and Societies*, vol. 8, no. 11, pp. 42–52, Nov. 2023, [Online]. Available: https://vectoral.org/index.php/IJSICS/article/view/97

[20] H. Liang, H. Song, H. Li, and Z. Dai, "Vehicle counting system using deep learning and multi-object tracking methods," *Transp Res Rec*, vol. 2674, no. 4, pp. 114–128, 2020, doi: 10.1177/0361198120912742.

[21] J. Manurung, N. Azizi, D. Anastasya, N. Valentino, A. Sanjaya, and K. Saputra, "Deteksi Kemacetan dengan Deep Learning YOLOv4 dan Euclidean Distance Tracker pada Jalan Raya di Kota Medan," *JUSTINDO (Jurnal Sistem dan Teknologi Informasi Indonesia)*, vol. 8, no. 1, pp. 57–63, 2023.

[22] J. J. Ng, K. O. M. Goh, and C. Tee, "Traffic Impact Assessment System using Yolov5 and ByteTrack," *Journal of Informatics and Web Engineering*, vol. 2, no. 2, pp. 168–188, 2023, doi: 10.33093/jiwe.2023.2.2.13.