An Intelligent System for Traffic Monitoring and Route Optimization Using YOLOv11, Random Forest, and Bee Colony Optimization

Sukemi *
Department of Computer Systems
Sriwijaya University
Palembang, Indonesia
sukemi@ilkom.unsri.ac.id

Ahmad Fali Oklilas
Department of Computer Systems
Sriwijaya University
Palembang, Indonesia
fali@ilkom.unsri.ac.id

M. Reza Arya Pratama
Department of Computer Systems
Sriwijaya University
Palembang, Indonesia
rezaarya2003@gmail.com

*Corresponding author
Received: 2025-09-12; **Accepted:** 2025-11-06

Abstract— **Traffic congestion is a major problem in Palembang City due to the significant growth in the number of vehicles. This study aims to develop an artificial intelligence-based system for detecting vehicle density and predicting optimal routes. Vehicle number detection is carried out using the YOLOv11 method based on CCTV data at 15 intersections in Palembang City, with training results showing an accuracy of 92%, F-1 Score of 82% and mAP@0.5 of 86.7%. In the validation and testing stages, this model achieved an accuracy of 90%, and mAP@0.5 of 81.7%. The detection data was then analyzed using the Random Forest (RF) algorithm to classify traffic conditions with a dataset of 769 rows of data, achieving an accuracy of 98.26%. Furthermore, the Bee Colony Optimization (BCO) algorithm was used to determine the fastest route by taking into account the distance traveled and the level of congestion. The results of the study show that the combination of the YOLOv11, RF, and BCO methods is able to produce an effective system in providing optimal route recommendations and helping to significantly reduce congestion. This system is expected to be a practical solution for city traffic management in the future.**

Keywords— Yolov11, Random Forest, Bee Colony Optimization, Vehicle density, Optimal route, Palembang City

I. INTRODUCTION

Traffic congestion is one of the main problems in big cities in Indonesia, including Palembang City, which is caused by the increase in the number of vehicles without being balanced by the development of adequate road infrastructure [1][2]. Based on 2023 data, the number of vehicles in South Sumatra Province reached more than 2.4 million units, with road conditions that are not all in good condition [1]. This problem has a direct impact on transportation efficiency, increased fuel consumption, long travel times, and other economic losses [3][4].

In addition, congestion also has a negative impact on the environment and public health, such as increased exhaust emissions and respiratory problems due to air pollution [5][6]. Therefore, it is necessary to develop an intelligent system that is able to detect traffic density and provide optimal route recommendations to reduce congestion.

Various studies have utilized digital image processing technology and artificial intelligence, one of which is through the You Only Look Once (YOLO) algorithm, which is popular for its ability to detect objects in real-time with high accuracy [7][8]. The latest versions, such as YOLOv8 and YOLOv11, show significant improvements in speed and precision compared to previous versions [9][10]. YOLO has also been widely applied in CCTV-based traffic monitoring systems [11][12].

However, vehicle detection alone is not enough. A classification model is needed to assess the level of traffic density based on the detection results. One effective method for classification is R, which is an ensemble learning algorithm based on decision trees and is known to have high performance in handling complex and heterogeneous data [13][14]. This algorithm can group traffic conditions into three main categories: smooth, moderate, and congested [15].

After classification, the next step is to determine the optimal route that not only considers the distance traveled but also the traffic density conditions. For this purpose, the BCO algorithm is used in this study. BCO is a metaheuristic algorithm inspired by the behavior of bees in searching for food and has been proven effective in solving path optimization problems [16][17][18].

The integration of these three components — YOLOv11 for vehicle detection, RF for density classification, and BCO for route optimization — creates a system that is able to analyze and respond to traffic conditions adaptively and in real-time [19][20]. The novelty of this study lies in the comprehensive integration of three components: YOLOv11 for high-accuracy real-time vehicle detection; RF for reliable congestion classification; and BCO for adaptive route optimization using empirical traffic data from Palembang City, for context-specific decision making. The proposed approach has been validated on 180 CCTV traffic videos and 12 time-based routing scenarios, demonstrating high detection accuracy and effective route recommendations.

II. METHODOLOGY

The following are the steps to classify traffic congestion using the RF algorithm and determine the optimal route using BCO as shown in Fig 1.

A. *Material and Equipment*

This research utilizes closed-circuit television (CCTV) video footage obtained from 15 intersections in Palembang City, provided by the Department of Transportation and the Land Transport Center Region VII of South Sumatra and Bangka

Belitung. The annotation process is supported by Roboflow to assist in labeling datasets with bounding boxes and class names. The detection model is trained using Google Colab and YOLOv11. Classification and optimization are performed using the RF algorithm and BCO, respectively, with data managed in Microsoft Excel.

B. *Amount of Data and Pre-Processing*

The dataset consists of 7,176 raw image files and 180 video recordings, all from CCTV surveillance on major roads. The images undergo four preprocessing stages: Data Cleaning, Data Integration, Data Transformation, and Data Reduction, resulting in 6,800 refined image samples ready for training. These samples are divided into training (80%), validation (10%), and testing (10%) datasets.

C. *Image Annotation*

Image annotation is performed using the Roboflow interface, which allows for bounding box placement and class labeling. The annotation output is stored in XML format following the PASCAL VOC standard.

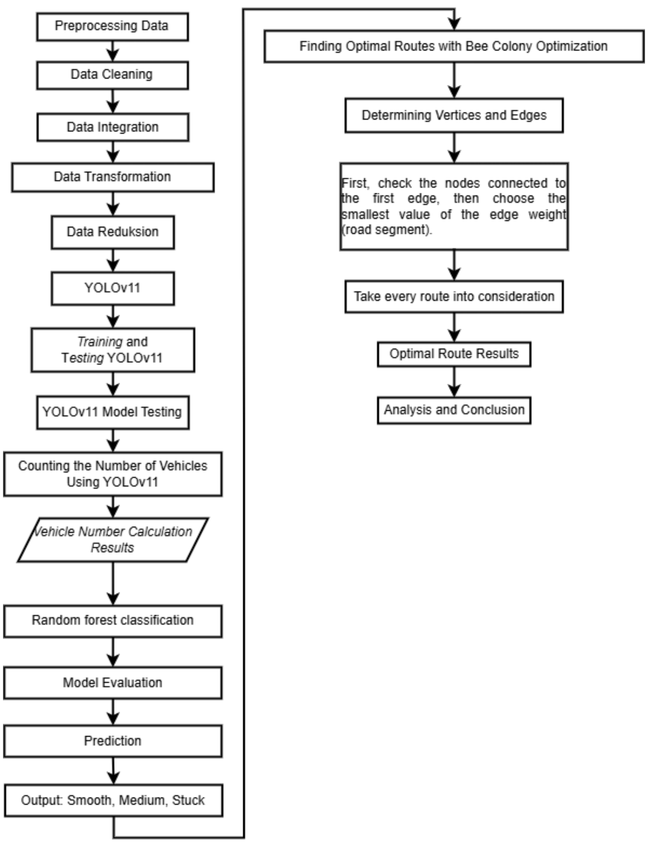

Fig. 1. Steps to Classify Congestion and Optimal Route

Five classes are defined in the dataset: Two-wheeled motorcycles, Three-wheeled motorcycles, Class One cars, Class Two cars, and Class Three cars. Annotation accuracy is critical to ensure effective model training and detection.

D. *Model Design*

1) YOLO is used for real-time object detection in image and video data. The model scans the input in a single pass using convolutional layers to predict bounding boxes and class probabilities. The model supports multi-scale detection, making it effective for detecting vehicles of various sizes. Evaluation metrics such as Precision, Recall, and F1 Score are calculated using the following formula:

$$Precision = \frac{true\ positive}{true\ positive + false\ positive} \tag{1}$$

$$Recall = \frac{true\ positive}{true\ positive + false\ negative} \tag{2}$$

$$F1\ Score = 2\left(\frac{precision * recall}{precision + recall}\right) \tag{3}$$

Where TP is true positive, FP is false positive, and FN is false negative [8][9].

1) RF is an ensemble-based algorithm consisting of many decision trees. RF is used for classification and regression tasks due to its ability to handle complex data. RF algorithm is described as a powerful and versatile machine learning method. This method falls under the category of ensemble learning, where a large number of decision trees are built and combined to improve prediction accuracy. This technique utilizes the bootstrap aggregating (or bagging) approach, which involves creating multiple subsets of training data through random sampling with replacement. In this context, RF is used to detect vehicles from visual data with high accuracy despite the heterogeneity of the data [21].

$$mtry1 = \frac{\sqrt{number\ of\ predictor\ variable}}{2} = \frac{\sqrt{4}}{2} = 1$$

$$mtry2 = \sqrt{number\ of\ predictor\ variable} = \sqrt{4} = 2$$

$$mtry3 = \sqrt{number\ of\ predictor\ variable \times 2} = \sqrt{4\ \times\ 2 = 4}$$

BCO is used to determine the optimal route by analyzing the weights of traffic conditions and distances between road segments. Inspired by the foraging behavior of honeybees, this algorithm evaluates candidate solutions and improves them iteratively to find the shortest and least congested route. This approach is efficient for real-time path finding in dynamic traffic scenarios.

III. RESULTS AND DISCUSSION

This research was conducted through several sequential stages, starting with image data processing, which includes data collection, preprocessing, annotation, model training, and object detection. After these steps are completed, the system proceeds to the video detection stage, where each processed video produces the number of detected vehicles. The vehicle count data is then tabulated using Microsoft Excel to determine the level of traffic density, which is then classified using the RF algorithm.

The training stage involves a dataset consisting of 5,440 images, which are used to train the YOLO model. The performance results of the YOLO-based detection system are illustrated in Fig. 3.

Based on the training result visualization, the precision curve achieved a peak value of 0.99 at a confidence threshold of 0.821, indicating the model's high capability in correctly identifying true positives. The recall metric recorded a value of 0.94, albeit at a lower confidence threshold of 0.000, reflecting the model's ability to capture most relevant instances despite the trade-off with confidence level. The F1-Score, which balances precision and recall, reached 0.82 at a threshold of 0.417, while the Precision-Recall (PR) curve produced an area under the curve (AUC) of 0.867 at 0.5 mAP, suggesting a reliable overall detection performance.

This checkpoint was subsequently used for evaluation on the test dataset, which consists of 10% of the total image samples. An example of the prediction results using this model is illustrated in Fig. 4, demonstrating the model's effectiveness in identifying and classifying vehicles under real-world traffic conditions.

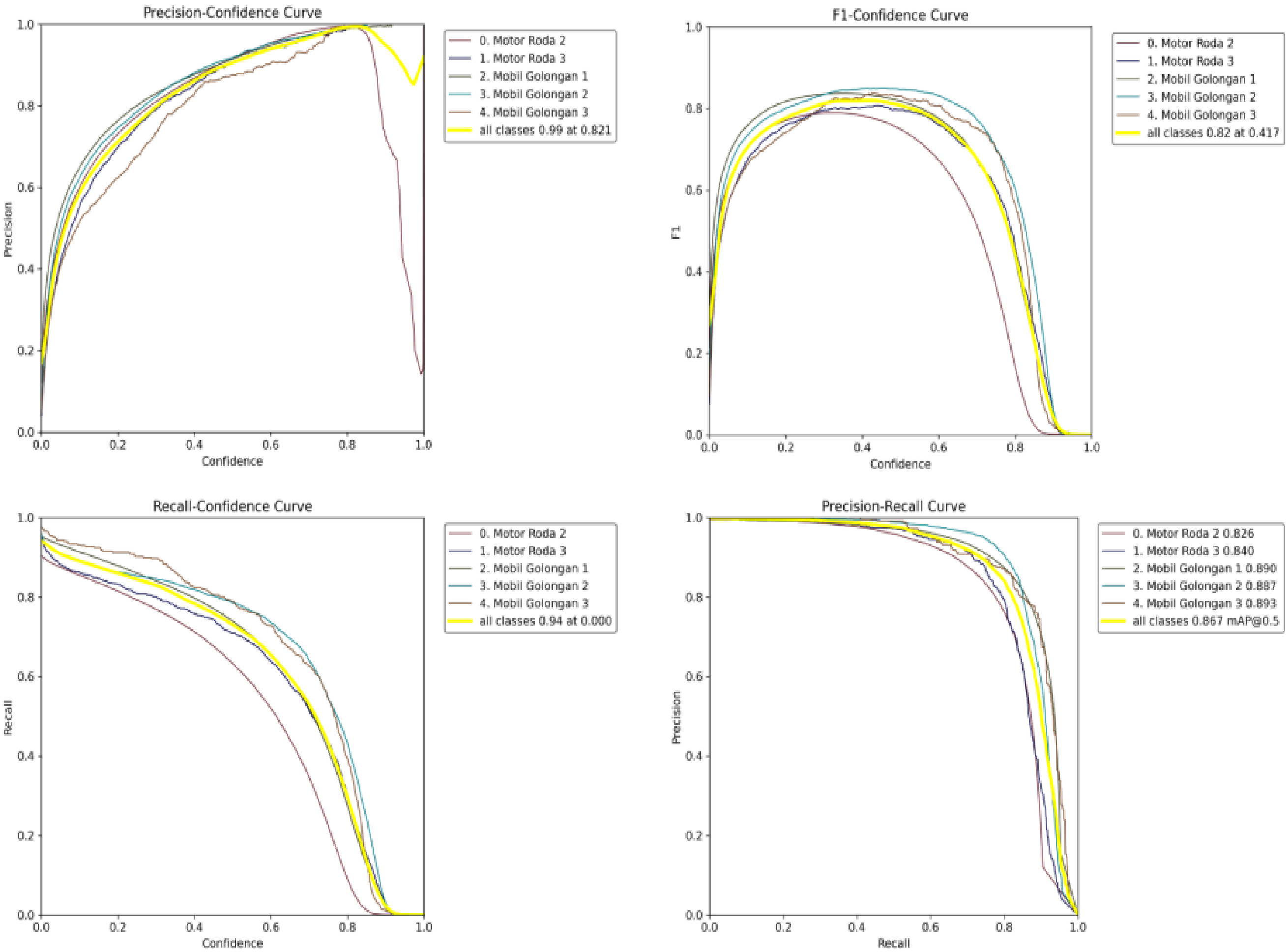

Fig. 3. YOLOv11 Training Results for Image Dataset

The trained model demonstrated high accuracy in detecting objects within images. However, a minor misclassification occurred wherein a rickshaw was incorrectly identified as a three-wheeled motorbike. This error is likely attributed to the strong visual similarity between the two vehicle types, particularly in their structural shape and size, which caused the model to misinterpret the rickshaw's features.

Following the successful implementation of image detection, the system was extended to process video data, where the model was tasked with detecting and counting the number of vehicles across multiple frames. The resulting output provided quantitative data on vehicle counts within each video segment. An example of this vehicle counting process based on video input is illustrated in Fig. 5, showcasing the model's application in dynamic traffic scenes.

Fig. 4. Example of Predict Result in Image

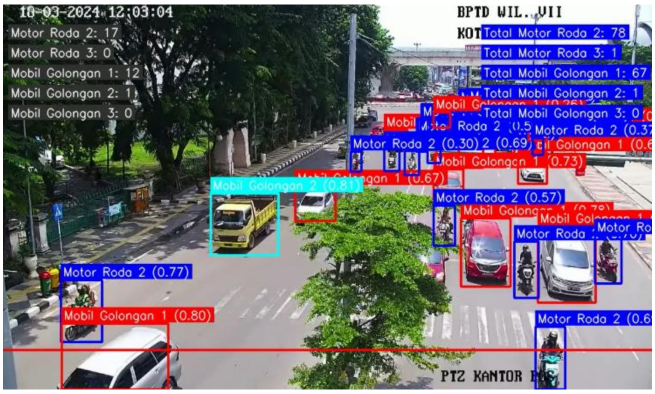

Fig. 5. Sample Vehicle Count Detection and Calculation on Video

The trained YOLOv11 model demonstrated reliable performance in detecting and counting vehicles from traffic video footage. The model successfully identified various types of vehicles, such as 2-wheeled motorcycles, 3-wheeled motorcycles, class 1 cars, class 2 cars and class 3 cars, and accurately counted the number of each vehicle crossing a pre-defined detection line. The output data from the detection process were systematically compiled and recorded using Microsoft Excel for further analysis. A summary of the vehicle counting results obtained from several video samples is presented in Table I used as the dataset.

The presented dataset consists of vehicle counting results obtained from video recordings with an average duration of about one minute, collected from various strategic locations in Palembang City. Each entry includes detailed information such as street name, date, recording time, and the number of detected vehicles, which are categorized into class 1 cars, class 2 cars, class 3 cars, motorcycles, and three-wheeled motorcycles, as identified using the YOLOv11 detection model.

TABLE I. CONGESTION CLASSIFICATION RESULTS ON VIDEO FOOTAGE

Cross roads	TIME	YOLO					Number of Road	Long Road	RF	Reference	Truth Value
		2 wheel motorbike	3 wheel motorbike	Class 1 Car	Class 2 Car	Class 3 Car					
Dempo	21.02.2024-06.30	39	1	14	3	0	3	850	Smooth	Smooth	1
	24.02.2024-06.30	1	0	12	0	0	3	850	Smooth	Smooth	1
	01.03.2024-06.30	25	0	22	0	0	3	850	Smooth	Smooth	1
	18.03.2024-06.30	10	0	29	0	0	3	850	Smooth	Smooth	1
Caritas	21.02.2024-06.30	72	1	43	1	0	3	2550	Busy Smooth	Busy Smooth	1
	24.02.2024-06.30	8	0	11	1	0	3	2550	Smooth	Smooth	1
	04.03.2024-06.30	37	0	45	0	0	3	2550	Busy Smooth	Busy Smooth	1
	15.03.2024-06.30	40	0	25	2	0	3	2550	Busy Smooth	Busy Smooth	1
Gerbang Terminal AAL	12.01.2024-07.03	154	18	88	28	10	3	3600	Smooth	Smooth	1
	13.01.2024-06.57	97	0	11	52	11	3	3600	Smooth	Smooth	1
	15.01.2024-07.12	137	1	102	40	7	3	3600	Smooth	Smooth	1
	17.01.2024-07.03	117	0	93	23	9	3	3600	Smooth	Smooth	1
Grand City	05.02.2024-06.30	27	0	44	9	1	3	1300	Smooth	Smooth	1
	21.02.2024-06.30	39	0	21	7	0	3	1300	Smooth	Smooth	1
	23.02.2024-06.30	29	1	22	6	2	3	1300	Smooth	Smooth	1
	02.03.2024-06.30	20	0	8	8	2	3	1300	Smooth	Smooth	1
Kambang Iwak	21.02.2024-06.30	64	0	20	0	0	2	1300	Smooth	Smooth	1
	24.02.2024-06.30	12	0	9	0	0	2	1300	Smooth	Smooth	1
	01.03.2024-06.30	72	0	20	0	0	2	1300	Busy Smooth	Busy Smooth	1
	18.03.2024-06.30	41	0	13	0	0	2	1300	Smooth	Smooth	1
Kantor Pos	15.03.2024-06.30	83	1	25	1	0	3	140	Busy Smooth	Busy Smooth	1
	16.03.2024-06.30	47	1	14	0	0	3	140	Smooth	Smooth	1
	18.03.2024-06.30	63	2	39	0	0	3	140	Smooth	Smooth	1

Cross roads	TIME	YOLO					Number of Road	Long Road	RF	Reference	Truth Value
		2 wheel motorbike	3 wheel motorbike	Class 1 Car	Class 2 Car	Class 3 Car					
	20.03.2024-06.30	86	0	38	0	0	3	140	Busy Smooth	Busy Smooth	1
Macan Lindungan	13.03.2024-05.46	70	0	66	11	0	3	8300	Smooth	Smooth	1
	15.03.2024-07.03	153	1	105	47	34	3	8300	Smooth	Smooth	1
	16.03.2024-06.42	123	2	83	37	0	3	8300	Smooth	Smooth	1
	18.03.2024-06.35	112	0	125	35	31	3	8300	Smooth	Smooth	1
Angkatan 45	04.03.2024-06.30	21	0	16	1	0	3	1900	Smooth	Smooth	1
	21.02.2024-06.30	28	0	13	0	0	3	1900	Smooth	Smooth	1
	23.02.2024-06.30	23	0	13	0	0	3	1900	Smooth	Smooth	1
	24.02.2024-06.30	35	0	15	0	0	3	1900	Smooth	Smooth	1
PIM	15.03.2024-06.31	33	0	6	0	0	3	450	Smooth	Smooth	1
	16.03.2024-06.24	32	3	2	0	0	3	450	Smooth	Smooth	1
	18.03.2024-06.34	27	1	6	0	0	3	450	Smooth	Smooth	1
	20.03.2024-06.39	48	1	12	0	0	3	450	Smooth	Smooth	1
Polda	05.02.2024-06.30	99	0	63	3	0	3	1000	Jammed	Jammed	1
	07.02.2024-06.30	150	1	63	1	2	3	1000	Jammed	Jammed	1
	23.02.2024-06.30	100	0	60	4	2	3	1000	Busy Smooth	Busy Smooth	1
	24.02.2024-06.30	99	1	48	3	0	3	1000	Busy Smooth	Busy Smooth	1
Rajawali	01.03.2024-06.30	16	0	21	3	0	3	1100	Smooth	Smooth	1
	04.03.2024-06.30	57	2	63	0	0	3	1100	Busy Smooth	Busy Smooth	1
	21.02.2024-06.30	73	2	53	0	0	3	1100	Busy Smooth	Busy Smooth	1
	24.02.2024-06.30	35	1	9	0	0	3	1100	Smooth	Smooth	1
Samsat	05.02.2024-06.30	39	2	42	1	0	2	650	Busy Smooth	Jammed	0
	15.03.2024-06.30	13	0	19	1	0	2	650	Smooth	Smooth	1
	24.02.2024-06.30	36	0	10	0	0	2	650	Smooth	Smooth	1
	28.02.2024-06.30	37	0	8	0	0	2	650	Smooth	Busy Smooth	0
Soekarno-Hatta	12.01.2024-06.50	42	0	29	4	6	3	6600	Smooth	Smooth	1
	13.01.2024-06.29	24	0	7	10	5	3	6600	Smooth	Smooth	1
	15.01.2024-07.11	74	0	15	10	1	3	6600	Smooth	Smooth	1
	17.01.2024-07.08	70	0	18	5	1	3	6600	Smooth	Smooth	1
Syailendra	01.03.2024-06.30	44	3	5	0	0	2	850	Smooth	Busy Smooth	0
	05.02.2024-06.30	72	3	8	0	0	2	850	Busy Smooth	Busy Smooth	1
	21.02.2024-06.30	109	2	13	0	0	2	850	Busy Smooth	Busy Smooth	1
	24.02.2024-06.30	17	1	13	0	0	2	850	Busy Smooth	Smooth	0
SP. WALIKOTA	15.03.2024-06.30	39	1	14	0	0	2	350	Busy Smooth	Busy Smooth	1
	16.03.2024-06.30	25	3	2	0	0	2	350	Smooth	Smooth	1

Cross roads	TIME	YOLO					Number of Road	Long Road	RF	Reference	Truth Value
		2 wheel motorbike	3 wheel motorbike	Class 1 Car	Class 2 Car	Class 3 Car					
	18.03.2024-06.30	8	2	19	1	0	2	350	Smooth	Smooth	1
	20.03.2024-06.30	36	3	17	0	0	2	350	Busy Smooth	Busy Smooth	1
Correct Prediction											162
Wrong Prediction											18
Prediction Accuracy											90.0%

The main result of this study lies in the classification of traffic congestion levels, which is carried out using the RF algorithm. The classification results, based on the number of detected vehicles and road attributes, are summarized in Table I.

The dataset consists of 180 rows and 12 columns, representing key traffic parameters at various intersections in Palembang. Each column includes attributes such as intersection location, recording time, number of vehicles detected by YOLOv11, road width, travel distance, RF prediction, manual reference labels, and ground truth indicators. These data collectively provide insights into traffic conditions at each location, based on the number and type of vehicles observed, as well as road characteristics.

For example, in the first entry, recorded at the Dempo intersection on February 21, 2024, at 06:30, the number of detected vehicles includes 39 two-wheeled motorcycles, 1 three-wheeled motorcycle, 14 class 1 cars, 3 class 2 cars, and 0 class 3 cars. With a road width of 3 meters and a travel distance of 850 meters, the Random Forest model predicts the traffic condition as "Smooth", consistent with the ground truth reference.

In the next stage of route optimization, the BCO algorithm is applied to evaluate six alternative travel routes from Ampera Bridge to Sultan Mahmud Badaruddin II International Airport. These routes differ in terms of total travel distance, infrastructure quality, and traffic density levels.

The process of selecting the optimal route considers not only travel distance, but also estimated travel time and ease of access, with the aim of offering the most efficient and convenient path for users. A graphical representation of the evaluated routes in Palembang City is presented in Fig. 6, which illustrates the spatial layout and connections of the alternative routes.

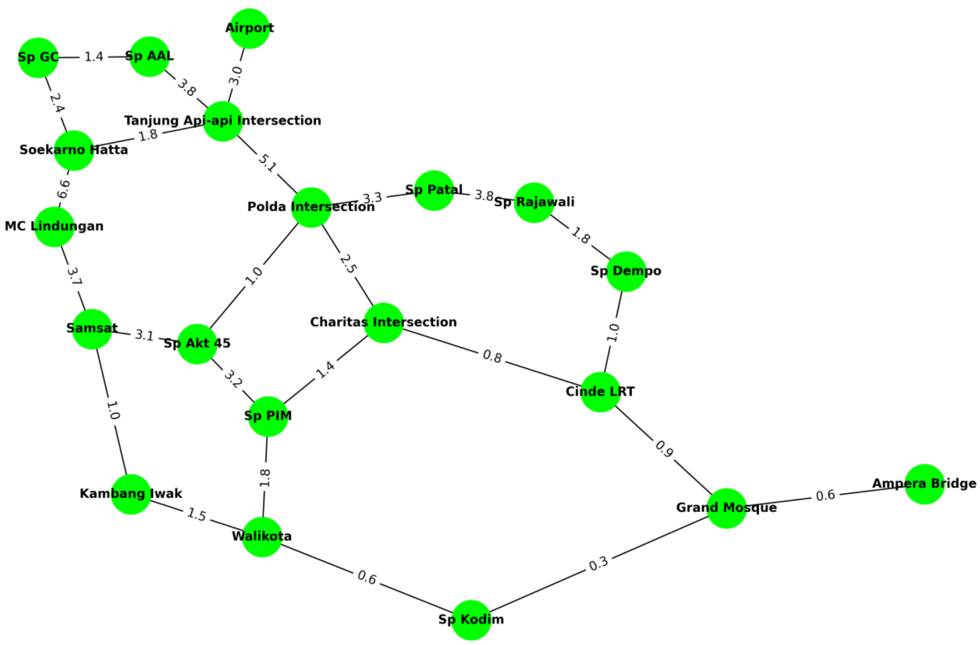

Fig. 6. Graphical Representation of Palembang City Routes

Based on the simulation results on 12 different time scenarios throughout the week, Route 1 emerged as the most frequently chosen route due to its lower cumulative traffic weight and relatively shorter travel distance. This route consistently offers optimal conditions at various levels of traffic congestion. The direction of Route 1 includes the following sequence: Ampera Bridge → Grand Mosque → Cinde LRT → Charitas Intersection → Polda Intersection → Tanjung Api-api Intersection → Airport. The spatial layout of these checkpoints is illustrated in Fig. 6, with a total average travel distance measured at approximately 15.9 kilometers.

The BCO algorithm consistently identifies routes with the lowest combined weight, which strengthens its reliability and adaptability in dynamic traffic environments. During weekdays, Route 1 is exclusively chosen and on weekends, Route 1 is also exclusively chosen, highlighting its consistent efficiency across various traffic conditions.

IV. CONCLUSION

This study successfully developed an intelligent traffic monitoring and route optimization system by integrating YOLOv11, RF, and BCO algorithms. The YOLOv11 model was effectively trained on vehicle image data captured from CCTV footage in Palembang City, achieving a training accuracy of 92%, F1-score of 82%, and mAP@0.5 of 86.7%. Performance remained consistent during validation and testing phases, with accuracy at 90% and mAP@0.5 at 81.7%. When applied to 180 real-world video samples across various locations and times, YOLOv11 maintained high average detection accuracy particularly over 90% for three-wheeled vehicles and higher-class cars, validating its robustness in diverse traffic conditions.

The RF classifier demonstrated strong generalization capabilities, with a training accuracy of 88.53% and predictive accuracy of 90.0% on actual traffic data. This model effectively categorized road conditions based on vehicle count, road width, and travel distance. In the final stage, BCO was used to determine optimal travel routes from Ampera Bridge to the airport. Out of 12 tested time scenarios, Route 1 was consistently selected as the best option due to its lowest cumulative weight and efficient structure. The route sequence—Ampera Bridge → Grand Mosque → LRT Cinde → Charitas → Polda → Tanjung Api-api → Airport—proved to be the most reliable and effective path based on real-time traffic data. The results demonstrate that the combination of YOLOv11, RF, and BCO provides a promising approach for real-time traffic density detection and adaptive route planning in urban environments such as Palembang City.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the author used *ChatGPT (OpenAI)* and *Grammarly* to assist with language refinement, grammar correction, and clarity of academic writing. After using these tools, the author thoroughly reviewed, verified, and edited the content as needed and takes responsibility for the integrity and accuracy of the published article.

REFERENCES

[1] S. C. Tirtowahjono and D. G. Purwanto, "Determining Traffic Flow Distribution at Intersections Based on Computer Vision & Deep Learning Technology," *J. Dimens. Pratama Tek. Sipil*, vol. 11, no. 1, 2022.

[2] R. Juliansyah, M. Aqil, and M. Ar, "Development of a Real-Time Traffic Density Detection Website Using YOLOv8-Based Digital Image Processing with OpenCV," *JISI*, vol. 6, no. 4, 2024.

[3] S. Xie and H. Sun, "Tea-YOLOv8s: A Tea Bud Detection Model Based on Deep Learning and Computer Vision," *Sensors*, vol. 23, no. 14, 2023, doi.org/10.3390/s23146576

[4] C. Reche, A. Tobias, and M. Viana, "Vehicular Traffic in Urban Areas: Health Burden and Influence of Sustainable Urban Planning and Mobility," *Atmosphere*, vol. 13, no. 4, 2022, doi.org/10.3390/atmos13040598

[5] D. A. Abdurrafi, M. T. Alawiy, and B. M. Basuki, "Vehicle Detection, Classification, and Counting Based on the YOLO Algorithm Using CCTV Cameras,"*Sci. Electro*, no. 1, 2023.

[6] P. Y. Putra et al., "Truck Vehicle Detection in Video Using Tiny-YOLOv4 Method," *J. Inform. Polinema*, vol. 9, no. 2, 2023, doi.org/10.33795/jip.v9i2.1243

[7] Y. Yanto, F. Aziz, and I. Irmawati, "YOLO-V8 Improved Algorithm for Face Mask Detection," *JATI*, vol. 7, no. 3, 2023, doi:10.36040/jati.v7i3.7047

[8] M. Cahyanti, "Vehicle License Plate Detection System with YOLOv8 Architecture," *Sebatik*, vol. 27, no. 2, 2023.

[9] M. R. D. Septian, "Implementation of Deep Learning Algorithm for Vehicle Count Monitoring System," *TEPIAN*, vol. 5, no. 4, 2024. https://doi.org/10.51967/tepian.v5i4.3213

[10] I. D. Mienye, T. G. Swart, and G. Obaido, "Recurrent Neural Networks: A Comprehensive Review of Architectures, Variants, and Applications," *Information*, vol. 15, no. 9, 2024, doi.org/10.3390/info15090517

[11] Y. Peng, Y. Liu, L. Yang, and L. He, "DProtoNet: Decoupling the Inference Module and the Explanation Module Enables Neural Networks to Have Better Accuracy and Interpretability,"*arXiv preprint*, 2022.

[12] G. Obaido et al., "An Improved Framework for Detecting Thyroid Disease Using Filter-Based Feature Selection and Stacking Ensemble," *IEEE Access*, vol. 12, July 2024, doi 10.1109/ACCESS.2024.3418974

[13] A. H. A. Al-Jumaili et al., "Big Data Analytics Using Cloud Computing Based Frameworks for Power Management Systems: status, Constraints, and future recomendations," *Sensors*, vol. 23, no. 6, 2023. doi.org/10.3390/s23062952

[14] S. S. Gill et al., "Modern Computing: Vision and Challenges," *Telematics and Informatics Reports*, vol. 13, 2024, doi.org/10.1016/j.teler.2024.100116

[15] R. T. Aruleba et al., "COVID-19 Diagnosis: A Review of Rapid Antigen, RT-PCR and Artificial Intelligence Methods," *Bioengineering*, vol. 9, no. 4, 2022, doi.org/10.3390/bioengineering9040153

[16] H. Wang et al., "Improved Multi-Dimensional Bee Colony Algorithm for Airport Freight Station Scheduling," *IEEE Access*, 2022, doi.org/10.48550/arXiv.2207.11651

[17] M. Flores-Calero et al., "Traffic Sign Detection and Recognition Using YOLO Object Detection Algorithm: A Systematic review," *Sensors*, 2024, doi.org/10.3390/math12020297

[18] Shenming Qu et al., "Improved YOLOv5-Based for Small Traffic Sign Detection Under Complex Weather," *Sensors*, 2023, doi.org/10.1038/s41598-023-42753-3

[19] J. Shen et al., "YOLOv5-TS: Detecting Traffic Signs in Real-Time," *Sensors*, vol. 11, 2023, doi.org/10.3389/fphy.2023.1297828.

[20] F. I. Sari et al., "Traffic Density Prediction Model: Comparison of Random Forest and XGBoost Algorithms,"*Jurnal Ilmiah Teknologi dan Sistem Informasi*, 2023.

[21] S. Mahmuda, "Implementation of the Random Forest Method on YouTube Channel Content Categories". *Jurnal Jendela Matematika*, vol. 2, no. 1. 2024, doi.org/10.57008/jjm.v2i01.633.