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Vehicle Classification in Electronic Toll Collection System Using YOLOv8

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Abstract

This research aims to initiate an automatization process in the method of classifying vehicle types in the Jasa Marga transaction service system, which is the largest toll road operator company in Indonesia. The method used is YOLOv8 which is the latest version of the YOLO algorithm which is state-of-the-art performance in image processing. The dataset used in this study consists of vehicle images obtained from transactional data in an electronic toll collection system operating on toll roads, comprising five vehicle classification classes. In the initial stage, the images are examined and processed using pre-processing techniques such as data cleaning, image masking and data annotation. Next, the YOLOv8 model is trained using the data and tested on a separate validation dataset to measure the model's performance. Based on the results of experiments that have been carried out in this research, the performance of the YOLOv8 model without handling imbalance data resulted in an accuracy of classification of vehicle class types of 91.4%, while the performance of the model that handled imbalance data using under-sampling resulted in an increase in classification accuracy of vehicle class types to 94.4 %.

Keywords: *Vehicle Detection, Vehicle Classification, Electronic Toll Collection, Computer Vision, YOLOv8*

1. Introduction

PT Jasa Marga (Persero) Tbk. is a Toll Road Business Entity (BUJT) primarily engaged in the operation and maintenance of toll roads. It holds 35 toll road operation concessions, with a total road length of 1,603 km, equivalent to 65.5% of the total operational toll road length in Indonesia. The toll fees are calculated based on the distance traveled and the vehicle classification on the toll road. Vehicle classification on the toll road refers to Minister of Public Works Decree Number 370/KPTS/M/2007 as seen in table 1. In table 1 it can be seen that the types of vehicle classes on Indonesian toll roads consists of five vehicle classifications based on the number of axles. Category two vehicles have special characteristics. Although they have the same number of axles as category one vehicles, they have thicker rear tires, commonly known as double tires. There is also a specific classification for buses, as they are considered large-sized vehicles and are categorized as category one on toll roads.

Table 1. Type of Vehicle Categories on Toll Roads

Vehicle Class	Vehicle Type
Class 1	Car, Jeep, Van, Small Truck, Bus
Class 2	Large Truck with 2 Axles
Class 3	Large Truck with 3 Axles
Class 4	Large Truck with 4 Axles
Class 5	Large Trucks with 5 Axles and more

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The Jasa Marga Electronic Toll Collection (ETC) system particularly for the Multi-Class Automatic Toll Booth (GTO), involves the determination and input of vehicle classifications by the operator personnel through direct visual observation or with the assistance of CCTV cameras and monitors within the toll booth [1]. This process determines the toll rates that need to be paid by toll road users. The automation of this process has been implemented within the Jasa Marga environment through the application of Automatic Vehicle Classification (AVC) [2]. Automatic Vehicle Classification (AVC) is a part of the ETC system that enables automatic identification of the vehicle classification passing through toll gates. The current method employs a combination of sensor detection technologies installed both beneath the road surface (in-roadway base) [3] and above the road surface (over-roadway base) [4], to detect vehicles and input the information into the system. This system has a high level of accuracy [5] in vehicle classification due to the sensors having close contact with the passing vehicles. However, the installation and maintenance of this system incur high costs [6] as it is located beneath the road surface. Maintenance or replacement of the equipment requires considerable time for opening and closing the road surface. Additionally, the installation or maintenance work can result in road closures or disruptions to traffic flow, affecting the toll gate's operations. Therefore, there is a need to develop a more cost-efficient vehicle classification technology with a minimum accuracy of 90% in classifying vehicle categories [7].

2. Related Works

In the journal related to vehicle classification technology, it is mentioned that vehicle classification systems can generally be categorized into three categories based on their application location: in-roadway based systems, over-roadway-based systems, and side-roadway-based systems. Figure 1 illustrates the classification of vehicle classification technologies [8].

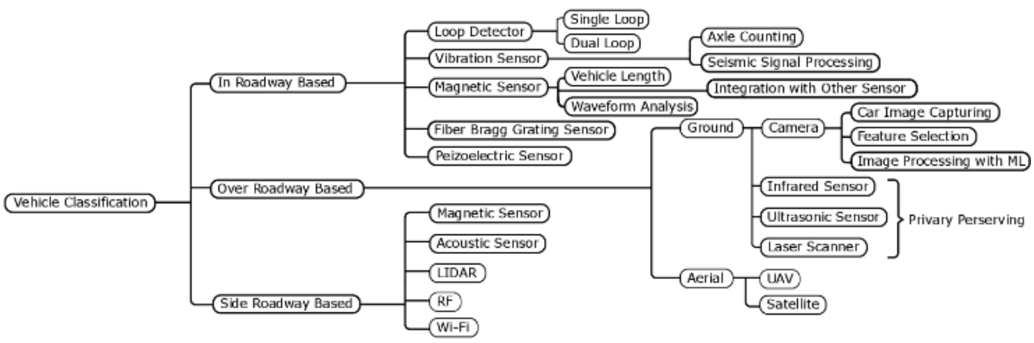

Figure 1. Vehicle Classification Scheme [8]

The over-roadway-based vehicle classification system, utilizing cameras, employs computer vision with image processing and machine learning [9]. The machine learning training process for vehicle classification involves the use of Convolutional Neural Network (CNN) [10], CNN is the most used type of artificial neural network in image processing tasks and pattern recognition. CNN can be utilized for vehicle classification on toll roads by taking vehicle images as input and providing labels as output [11]. You Only Look Once (YOLO) is a real-time object detection method in images that utilizes CNN. The YOLO method utilizes CNN to divide the image into multiple grids and then generates predictions of bounding boxes and object classes for each grid. This method enables fast and accurate object detection [12].

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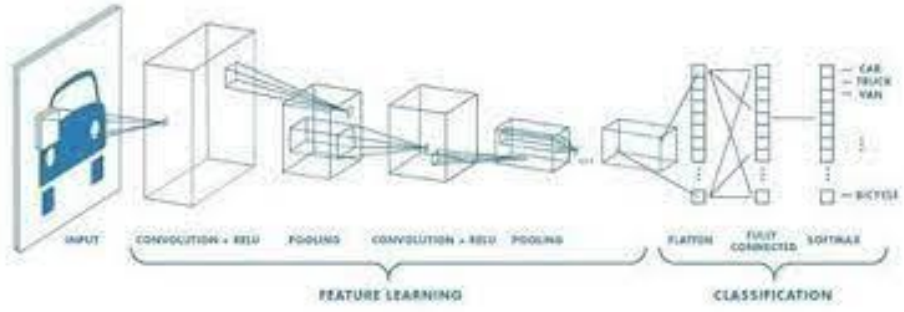

Figure 2. Convolutional Neural Network Architecture [13]

In a research study conducted in 2019, real-time vehicle counting was implemented using a method that divided the road into monitoring zones. The detected vehicles were then directly moved using the YOLO framework. Subsequently, the detected vehicles were tracked using Kalman filter and Hungarian algorithm. The achieved accuracy level exceeded 90% for most tested videos. The average speed was approximately 32 frames per second (fps), which is the normal real-time speed [14].

In 2021, a research YOLOv4 method for vehicle detection and traffic flow counting in transportation in Vietnam was conducted. The study aimed to classify five types of vehicles, including motorcycles, bicycles, cars, trucks, and buses. The testing results showed that the algorithm achieved a 99.4% accuracy in vehicle detection [15].

In 2022, a research study on vehicle identification and classification on Indian toll roads was conducted using the deep learning algorithm YOLOv3. The algorithm was trained on a dataset of vehicles that included different vehicle classes according to the classification of vehicles on Indian toll roads. The classification accuracy achieved was up to 94.1%[16].

In a study conducted in 2022, YOLOv4 and Mask R-CNN were employed for detecting damage on commodity bags, with the detected object classes being the bags and holes on the bags. Testing was performed on 20 test datasets, comparing the results to manual calculations by humans. The findings revealed that the YOLOv4 model outperformed, achieving an accuracy of 96.8%, while the Mask R-CNN model exhibited less reliable performance with an accuracy of 65.78% on the same test data [17].

In 2022, a research study was conducted on the real-time classification of vehicle types in Indonesia using the YOLOv5 method. The study focused on classifying vehicles such as bajaj (auto-rickshaw), becak (cycle rickshaw), bus, car, concrete mixer truck, pickup truck, bicycle, motorcycle, and truck. The results showed a relatively high level of accuracy, reaching 90%[18].

In 2023, a research study proposed a YOLOv8 model approach for the identification and detection of nine vehicle classes in a reprocessed image dataset. The process involved adding labels to a dataset comprising 2,042 training images, 204 validation images, and 612 test images. Following training, the model achieved an accuracy value of 77% using the settings: epoch = 100, batch = 8, and image size of 640 [19].

In 2023, a research study proposed a new approach for vehicle detection and classification using aerial image sequences, consisting of five stages: pre-processing to reduce noise and enhance brightness, segmentation to extract foreground items, vehicle detection employing the YOLOv8 algorithm, feature extraction using SIFT, ORB, and KAZE features, and classification utilizing a DBN classifier. Experimental results demonstrated promising outcomes with the proposed model achieving 95.6% accuracy on the VEDAI dataset and 94.6% on the VAID dataset.[20].

In 2023, a study introduced an adaptive traffic signalization approach based on YOLOv8, a convolutional neural network architecture, departing from conventional fixed-duration systems. By leveraging computer vision with deep learning, real traffic imagery from ten intersections formed the basis for training the deep neural network, with image labeling encompassing seven distinct classes: car, bike, SUV, van, bus, truck, and person. Using Python programming, the software employed the coordinate data of bounding boxes to determine the number of vehicles awaiting signal changes. Subsequently, the duration of green lights was dynamically adjusted based on the vehicle count and classification scores, rather than adhering to a static duration. The proposed method demonstrated an object detection and classification accuracy of 91%, with anticipated benefits including reduced waiting times at red lights, diminished fuel consumption, lower air pollution levels, decreased driver stress, and fewer traffic incidents, ultimately addressing numerous traffic-related challenges [21].

YOLOv8[22] was released in January 2023 by Ultralytic, which also developed YOLOv5. YOLOv8 introduces improvements in the form of a new neural network architecture. Two neural networks, namely Feature Pyramid Network (FPN) and Path Aggregation Network (PAN), along with new tools for annotation that simplify the annotation process. This annotation tool contains several useful features, such as automatic labeling, shortcut labeling, and customizable hotkeys. The combination of these features makes it easier to annotate images to train models. FPN works by gradually reducing the spatial resolution of the input image while increasing the number of feature channels. This results in the creation of a feature map that can detect objects at different scales and resolutions. On the other hand, PAN architecture can combine features from different network levels through skip connections. As a result, the network can more effectively capture features at multiple scales and resolutions, which is critical for accurately detecting objects of various sizes and shapes [23]. YOLOv8 is available in five versions, namely YOLOv8n (nano), YOLOv8s (small), YOLOv8m (medium), YOLOv8l (large) and YOLOv8x (extra-large). YOLOv8 can support various computer vision tasks such as object detection, segmentation, tracking, and classification.

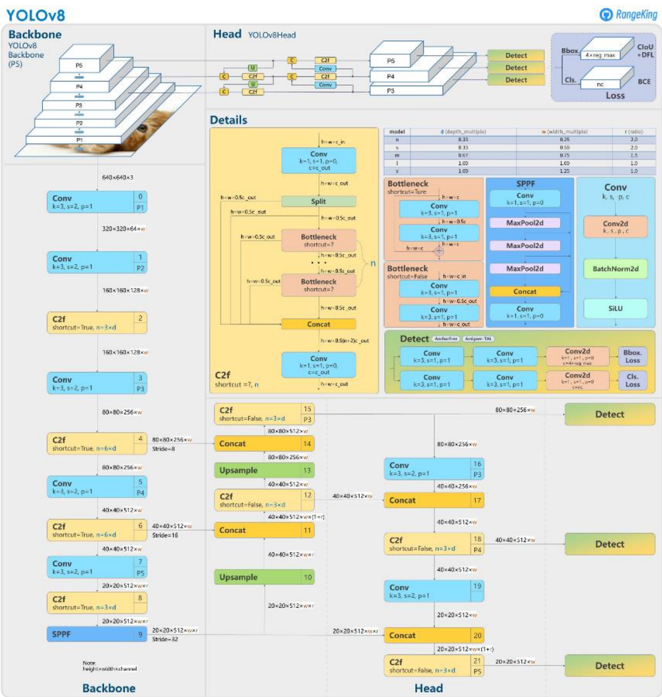

Figure 3. YOLOv8 Architecture [24]

YOLOv8 on the backbone is like YOLOv5 with some changes to the CSPLayer, which is currently called the C2f module. The C2f (cross-stage-partial bottleneck with two convolutions) module combines high-level features with contextual information to improve detection accuracy. YOLOv8 uses an anchor-free model with a separate head to process objectivity, classification, and regression tasks independently. This design allows each branch to focus on its tasks and improves overall model accuracy. In the output layer of YOLOv8, they use the sigmoid function as the activation function for the objective score, which represents the probability that the bounding box contains an object. It uses a softmax function for class probabilities, representing the probability of an object belonging to each possible class. YOLOv8 uses CIoU and DFL loss function for bounding box loss and binary cross-entropy for classification loss. This loss has improved object detection performance, especially when dealing with smaller objects. YOLOv8 also provides a semantic segmentation model called the YOLOv8-Seg model. The backbone is a CSPDarknet53 feature extractor, followed by a C2f module, instead of the traditional YOLO neck architecture. The C2f module is followed by two segmentation heads, which learn to predict semantic segmentation masks for the input image. This model has a detection head similar to YOLOv8, which consists of five detection modules and one prediction layer. The YOLOv8-Seg model has achieved state-of-the-art results on various object detection and semantic segmentation benchmarks while maintaining high speed and efficiency. YOLOv8 can be run from the Command Line Interface (CLI), or it can be installed as a PIP package. Additionally, it comes with various integrations for labeling, training, and deployment. Evaluated on the MS COCO test-dev 2017 dataset, YOLOv8x achieves AP of 53.9% with an image size of 640 pixels (compared to 50.7% YOLOv5 on the same input size) at 280 FPS on NVIDIA A100 and TensorRT [22].

3. Research Methodology

This research focuses on developing vehicle classification in the Electronic Toll Collection (ETC) system using YOLOv8 to classify vehicle types on toll roads. This research can contribute to the initiation of the automation process in classifying vehicle types in the transaction service system, which is currently still mostly done manually in the service company environment, so that it can contribute to increasing the efficiency of the company's toll transaction management business process. The stages in this research consist of five stages, namely the planning stage, initiation stage, training stage, performance improvement stage and evaluation stage. The research consists of five stages: planning, initiation, training, performance improvement, and evaluation. These stages are illustrated in detail in Figure 4, depicting the step-by-step process of the research.

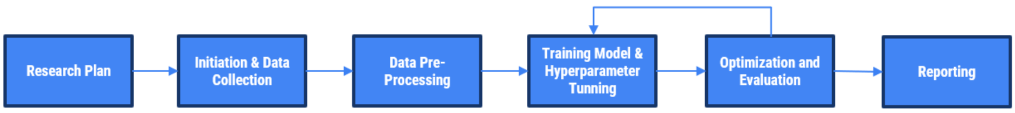

Figure 4. Research Stages

This research begins with the research planning phase, where the research idea is derived from the experience gained while working at PT Jasa Marga company, specifically in the field of operational technology. Solutions to the identified problems are obtained through literature studies and modeling studies, which form the basis of this research.

In the initiation phase, dataset collection is conducted by gathering toll transaction data and vehicle photos at toll gates. The toll transaction data contains vehicle classification information inputted by operators through the toll transaction equipment system, along with the corresponding vehicle photos. The model development phase aims to build a model using the proposed method, which is YOLOv8.

At the data pre-processing stage, all data that has been collected will be data cleaned for data with poor image quality due to technical errors or weather factors. After this process is complete, the next process is the image masking process to reduce detection errors or focus vehicle detection and classification only on the desired road lane.

Next, the training phase involves training the model using the data set that has been completed in the previous process. This data will undergo data annotation or class labeling to ensure that the model can correctly identify vehicle objects according to their classification categories. In the training process, hyperparameter tuning will also be carried out to find which parameters are the most optimal.

The research ends with the optimization and evaluation stage, where there are other efforts that can be made to improve the performance of the model, then the model performance metrics will be measured and recorded to be included in the research report.

In this research, the method for classifying vehicle types in the proposed transaction service system uses YOLOv8, apart from that we will also obtain the parameters that have the most influence on the accuracy performance of the model and what optimizations can be carried out. The stages of implementing the method proposed in this research can be seen in Figure 5 below.

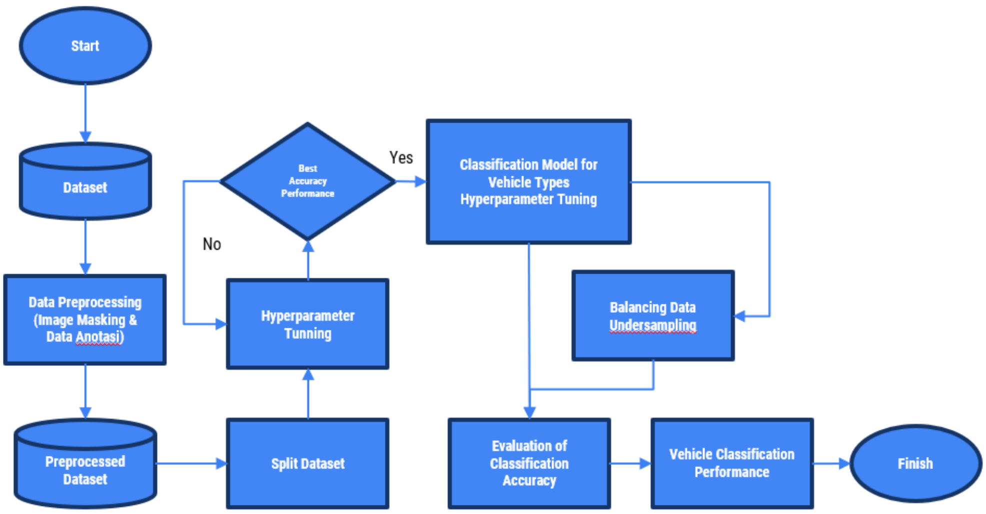

Figure 3. Proposed Methods

After the entire dataset has been data preprocessed, the entire dataset will be divided into three parts consisting of training set, validation set and test set using the parameters 80% training set, 10% validation set and 10% test set. The evaluation in this research is divided into two stages, the first stage is the evaluation stage of model training with validation set data. Evaluation of classification accuracy for 5 classes of vehicles on toll roads from the validation set, using confusion matrix by calculating the resulting accuracy value based on the classification model that has been annotated on the training data, if the evaluation of accuracy results with the validation set data has not yet obtained an average accuracy value of all the expected classes, which is more than or equal to 90%, then to increase the accuracy value, optimization will be carried out by adding training datasets, adding preprocessing data, hyperparameter tuning or optimizing the proposed model. This accuracy value measures how accurate the model is in classifying the types of vehicle groups that will carry out transactions at the toll gate. The higher the

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accuracy value, the better the model performance. If the accuracy performance of the model has reached an average accuracy result of equal to or more than 90%, the next process can be tested using the test set data. The results of the classification model obtained are in the form of predicted images of vehicle classes equipped with the position of the bounding box created for images of vehicles that have been successfully detected and recognized. In addition to the prediction results image, a measure of the accuracy performance of the model for each class will be recorded and evaluated.

From the results of the evaluation data, it was found that there was less data with the category 4 type class label than the other vehicle type class labels. Next, a data balance check was carried out using visualization techniques to be able to describe the percentage distribution of the class dataset for the types of vehicles owned. The results of the visualization carried out can be seen in Figure 6 below.

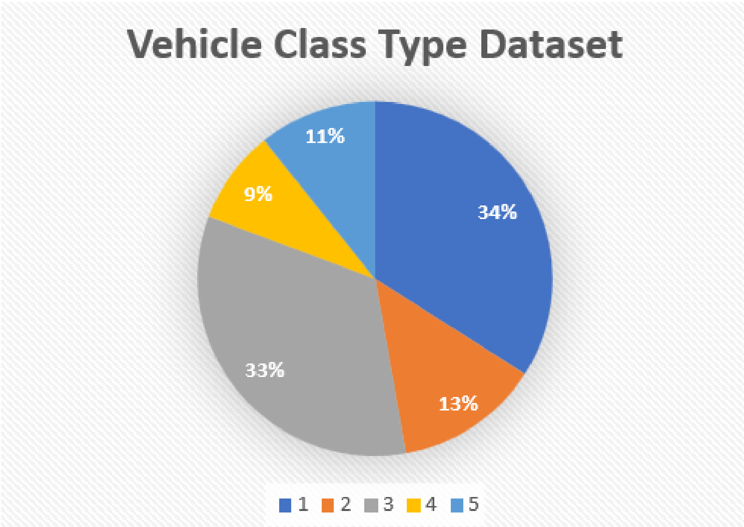

Figure 4. Percentage Distribution of Vehicle Type Dataset

Based on the visualization carried out, there is imbalanced data. The use of imbalanced data can affect the performance of the algorithm used [25], so on this basis a process to overcome data imbalance is carried out so that the dataset used in the vehicle class classification process is balanced. At this stage, the process of overcoming the data imbalance problem is carried out using the random under-sampling method. In the random under-sampling method, some data from larger classes (other than group 4) is deleted. This is done until all classes have the same or balanced amount of data.

After the amount of data for all classes has been balanced, the training process of the model will be carried out again using hyperparameter tuning which has been carried out previously from model testing without balancing data, the experiment ends by carrying out the process, this process will carry out a comparison between the accuracy performance of the vehicle type classification model and the data the imbalance and the classification model for vehicle types with data that is balanced.

4. Results and Discussion

From the data preprocessing process, the entire dataset will be split or divided into 80% training set data, 10% validation set data and 10% test set data with details of the amount of data for all classes as shown in table 2.

Table 2. Distribution of datasets with predetermined proportions

Class Type	**Amount Dataset**	**Training Set 80%**	**Validation Set 10%**	**Test Set 10%**
Amount Dataset	1.379	1.103	138	138
Class 1	469	383	48	38
Class 2	182	149	10	23
Class 3	462	362	57	43
Class 4	118	92	12	14
Class 5	148	117	11	20

After the data splitting process has been completed according to table 2. The next process is the training stage of the YOLOv8 model with the most optimal hyperparameters tunning. This training process functions to make the YOLOv8 model able to detect and classify vehicle types according to the predetermined class types, while improving the performance of the model. In this experiment, the hyperparameter values that have been tested are as explained in table 3.

Table 3. Accuracy performance comparison between different hyperparameters

Parameter			**Average Accuracy**
Epochs	**Image Size**	**Batch Size**	
100	640	24	91.40 %
		32	84.60 %
		48	88.80 %

Based on the results of experiments that have been carried out using hyperparameters with different batch size parameter values as seen in table 4.2. The parameters that describe the performance of the YOLOv8 model for classifying vehicle types with the highest accuracy values are epoch = 100, Image Size = 640, Batch Size = 24, with the average accuracy performance for all model classes being 91.40%.

4.1. Classification Model Performance with Imbalanced Data

Based on the most optimal tuning hyperparameters that have been carried out and explained in the previous section, these parameters are used to test the YOLOv8 model to classify vehicle types based on predetermined classes. The classification results of the model can be seen in the confusion matrix in Figure 7.

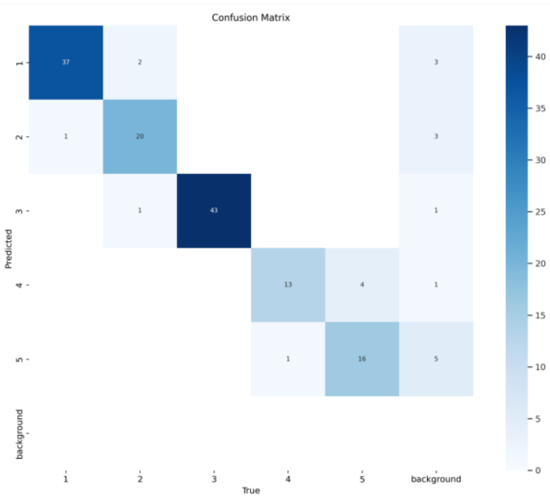

Figure 5. Confusion Matrix YOLOv8 classification results with imbalance data

Based on figure 7. The results of the classification of vehicle types from the YOLOv8 model can be seen using the test set data that has been prepared. The accuracy performance of the model for classifying vehicle types in detail can be seen in table 4.

Table 4. Classification accuracy performance based on vehicle type class

Class Type	Test Set	Correct	Accuracy
Class 1	38	37	97.00 %
Class 2	23	20	87.00 %
Class 3	43	43	100.00 %
Class 4	14	13	93.00 %
Class 5	20	16	80.00 %
	Average Accuracy		91.40 %

Based on the model classification results seen in table 4. The best classification results were in class 3, an accuracy value of 100% was obtained from all 43 test data, all of which could be classified according to the vehicle type class. In class 1 and type 2 classes the classification accuracy performance of the model can reach more than 90%, while for class 2 and class 5 the accuracy performance is less than 90%.

4.2. Classification Model Performance with Under-sampling

Based on the analysis and visualization of the population dataset that has been explained in section 5, there is a data imbalance in the group 4 class data set which has a smaller amount of data compared to other group classes, so that in the next experiment random under-sampling or reducing the amount of data will be carried out. in classes 1, 2, 3, 5 follows the total data for class 4, and continues with splitting the data as shown in table 5.

Table 5. Dataset distribution with balanced data

Class Type	Total Dataset	Training Set 80%	Validation Set 10%	Test Set 10%
Class 1	118	94	12	12
Class 2	118	94	12	12
Class 3	118	94	12	12
Class 4	118	94	12	12
Class 5	118	94	12	12

From the results of splitting or dividing data in table 5. and the most optimal hyperparameter tuning which has been carried out and explained in table 3. These parameters are used again to optimize the YOLOv8 model to classify vehicle types based on class which has been done previously without balancing the under-sampling data. The classification results of the model can be seen in the confusion matrix in Figure 8.

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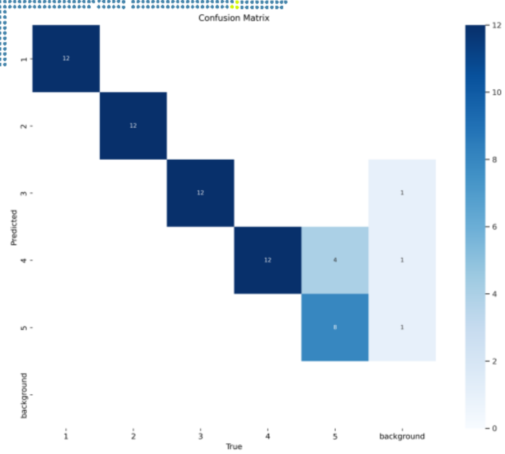

Figure 6. Confusion Matrix YOLOv8 classification results with Under-sampling

Based on figure 8, the results of the classification of vehicle types from the YOLOv8 model can be seen on the test set data which has been balanced with under-sampling. The accuracy performance of the model for classifying vehicle types in detail can be seen in table 6.

Table 6. Classification accuracy performance based on vehicle type class

Class	Test Set	Correct	Accuracy
Class 1	12	12	100.00 %
Class 2	12	12	100.00 %
Class 3	12	12	100.00 %
Class 4	12	12	100.00 %
Class 5	12	8	67.00 %
		Average Accuracy	93.40%

Based on the results of the model classification performance with under-sampling which can be seen in table 6. The results of the classification accuracy performance for label classes 1, 2, 3, 4 have an accuracy value of 100%, obtained from all 12 data test for each class, all of which can be classified according to the vehicle type class. In class 5, the classification accuracy performance of the model is 67%, which means that from 12 test data, 8 vehicle image data can be classified correctly according to class 5 vehicle class and there are 4 image data that are incorrectly classified.

5. Conclusion

Based on the experiments carried out in this research, the vehicle type classification model for the transaction service system using YOLOv8 can perform fairly accurate classification tasks with an accuracy performance of 91.4%. Optimizing model performance by balancing the dataset using an under-sampling approach can increase the accuracy performance of the model to 93.4%. The low accuracy rate occurs for the classification of vehicle classes with more than 2 axles, which is due to the limitations of the camera angle in displaying the number of rear wheels of the vehicles and the lack of datasets for those specific vehicle categories.

For further research, it is recommended to create a separate model for the classification of vehicles with more than 2 axles, which would improve the accuracy of the model for classifying vehicles based on their profiles. Adding a camera to provide better focus on the axle objects could also be a solution to improve accuracy.

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