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EXAMINING THE PERFORMANCE OF A DEEP LEARNING MODEL UTILIZING YOLOV8 FOR VEHICLE MAKE AND MODEL CLASSIFICATION

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Abstract

Vehicles are important inventions that greatly improve various aspects of human life and find use in almost every field. Once tools are introduced to human existence, they enable time-saving and tasks that are complex or cannot be accomplished by human power. It can be used in situations such as classification of vehicles and tracking of escaped drivers. Tracking the vehicles with the help of brand and model will provide distinctive information to traffic officers. In addition, vehicles of different sizes and functions in traffic can be directed to different lanes. This study examines the use of a YOLOv8 (You Only Look Once version 8) based deep learning model and evaluates its performance for vehicle brand and model classification. YOLOv8 is known as an effective method in the field of object detection and is used in this study to classify the make and model of vehicles. In the classification, 94.3% classification accuracy was achieved.

Keywords: Vehicle make and model recognition, deep learning, YOLOv8, classification

1. Introduction

Vehicles are one of the indispensable elements in every aspect of our lives. In this case, vehicles cause problems in traffic because they are on the road, and not every user pays attention to the rules while driving. Vehicle identification systems are gaining importance day by day for reasons such as minimizing accidents by preventing those who do not comply with the rules, being able to be examined statistically, distinguishing vehicle types at toll gates, and security reasons. Vehicle identification plays an important role in intelligent traffic systems. When we look at the market, there are a wide variety of vehicle brands and models [1].

Automatic classification of vehicles through vehicle brand and model identification systems is one of the longstanding problems. Many studies have been done in this field to cope with this challenge, but the main problem here is the large number of classes. In order to better deal with this problem in terms of relevant vehicle-specific challenges, vehicle-specific information should be well-researched and used to solve this problem [2].

In recent years, developing image-based vehicle classification methods using deep learning has attracted the attention of many researchers as it offers an efficient and adaptable approach [3].

The study uses a large dataset to evaluate the performance of the deep learning model. This dataset contains images of various vehicles of different makes and models. The YOLOv8 model was trained on these images and then tested.

The results of the study evaluate the success of the YOLOv8 model in the task of vehicle brand and model classification. The results are presented by analyzing the model on performance metrics such as accuracy, precision, and recall. Additionally, analyses performed to identify potential challenges and improvement opportunities for the model are also summarized.

This study makes a significant contribution to understanding and improving the performance of the deep learning-based YOLOv8 model in the task of vehicle brand and model classification. By evaluating the strengths and weaknesses of the model, guiding information is provided for future studies.

2. Literature review

In this section, ground studies in the literature are included.

In their study, Ali et al. [4] classified 48 classes with pre-trained deep-learning models using a dataset containing 3847 images of different vehicle brands and models. In the analysis, ResNet 50, ResNet152, MobileNet, and VGG16 pre-trained deep learning models were used. They achieved 74.32% classification accuracy with VGG16.

In their study, Manzoor et al. [5] used a data set containing 3859 images consisting of 35 classes of different vehicle brands and models and classified them with pre-trained deep learning models. While HOG (Histogram of Oriented Gradients) and GIST (Gist Feature Descriptor) were used as feature extraction methods in the analysis, RF (Random Fores) and SVM (Support Vector Machine) machine learning models were used for classification. They achieved the highest classification accuracy of 97.89% with SVM.

In their study, Hassan et al. [6] used a dataset containing 16185 images of different vehicle brands and models with 196 classes and classified them with pre-trained deep learning models. ResNet-152, Inception-ResNet-v2, Xception, DenseNet-201, MobilNet-v1, and DenseNet-121 pre-trained deep learning models were used in the analysis. The highest classification accuracy of 93.96% was achieved with DenseNet-201.

In their study, Bhujbal et al. [7] detected a dataset consisting of 4 different vehicle types and containing 2659 images with deep learning models. Fast Regional Convolutional Neural Network, YOLO and Fast Deep Neural Network deep learning models were used in the analysis. An 87% object detection success rate was achieved with Sighthound.

Ren et al.'s study [8] used deep learning models to classify a data set of 29847 photos and 233 classes from various car brands and models. They used local binary pattern (LBP), local gabor binary patterns (LGBP), Scale-invariant Feature Transform (STFT), Linear SVM, RBM, CNN, TCNN and MMR models in the analysis. The highest classification accuracy of 98.70% was achieved with MMR.

The study conducted by Luo et al. [9] consists of two scenarios. In the first scenario, the 998 class data set containing approximately 90000 images of different vehicle brands and models, and in the second scenario the 500 class data set containing over 5000 images of vehicle faces were classified with pre-trained deep learning models. In the analysis, 8-layer AlexNet and 9-layer AlexNet pre-trained deep learning models were used. The highest classification accuracy was achieved with 9-layer AlexNet as 97.51% in the first scenario, and 91.22% with 9-layer AlexNet in the second scenario.

In their study, Jamil et al. [10] Jamil used 6639 photos of various car brands and models to classify 29 classes using machine learning models. As a classifier, they employed the SVM machine learning model. SVM produced a classification accuracy of 98.22%.

In their study, Abbas et al. [11] used a data set consisting of 20 classes and over 3000 images of various vehicle brands and models and classified them with machine learning models. In the analysis, they achieved 97.31% classification accuracy with the KNN model.

Fomin et al. [12] used a dataset of 16185 photos of various car makes, models, and types to classify 169 classes using deep learning models. The analysis employed the VGG-16, ResNet, and YOLO models; the VGG-16 model had a classification accuracy of 92.60%.

In their work, Ni et al. [13] used deep learning models to classify a data set including 416,314 photos and 149 classifications, which included various car brands and models. Using the ResNet50 deep learning model, 96.20% classification accuracy was attained in the analysis.

In their study, Boonsim and his colleagues [14] classified 766 images taken in dark and low-light environments with machine learning models using a data set consisting of 421 classes of different vehicle brands and models. SVM, DT, and KNN deep learning models were used in the analysis, and 93.80% classification accuracy was achieved with SVM.

Similar studies conducted in this field are given in Table 1.

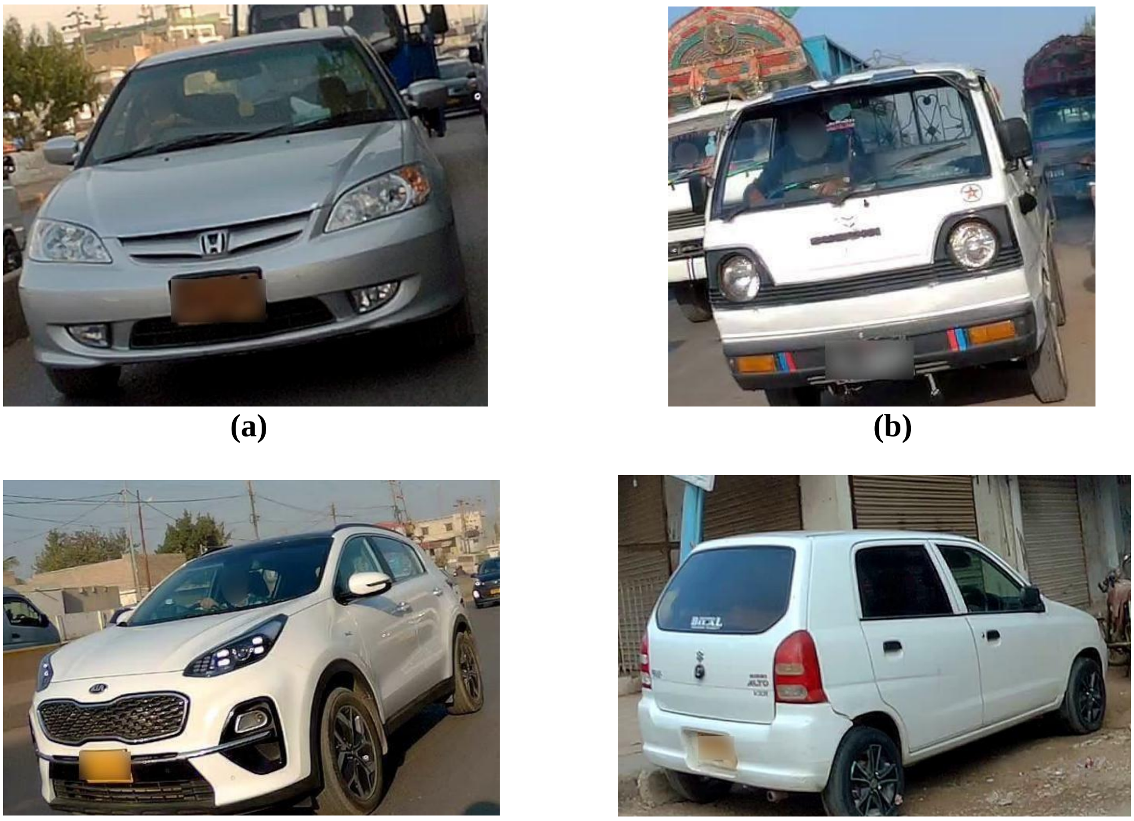
Table 1. Literature review.

Class	Methods	Accuracy	References
48	ResNet50 ResNet152 MobileNet VGG-16	67.13% 69.24% 73.54% 74.32%	[4]
35	RF	94.53%	[2]

	SVM	97.89%	
196	ResNet-152 Inception-ResNet-v2 Xception DenseNet-201 MobilNet-v1 DenseNet-121	92.81% 92.91% 93.13% 93.96% 93.02% 91.82%	[3]
4	Fast regional convolutional neural network YOLO Fast deep neural network	86.20% 87.00% 66.90%	[5]
233	Local binary pattern(LBP) Local gabor binary pat terns(LGBP) Scale-invariant feature transform(STFT) Linear SVM RBM CNN TCNN MMR	46.30% 68.90% 77.80% 88.10% 88.30% 87.50% 91.30% 98.70%	[6]
998 500	Eight Learned Layers AlexNet Nine Learned Layers AlexNet	90.57%(Top-1) 97.51%(Top-5) 91.22%(Top-5)	[7]
29	SVM	98.22%	[8]
20	kNN	97.30%	[9]
169	VGG-16 Resnet Yolo	92.60%	[10]
149	ResNet50	96.20%	[11]
421	SVM	93.80%	[12]
48	YOLOv8n	94.3%	Our Study

3. Material and methods

In the study, the vehicle make and models (VMM) dataset, which contains images of car models, was used [4]. There are 48 classes in this data set. These classes include models of various cars from different years. Classes of the data set; It consists of 48 brands and models such as Honda Civic 2015, Suzuki Cary, and Daihatsu Core. There are 3847 images of various car makes and models in the dataset. The sizes of the images in the data set vary. Images are in JPG format, 24-bit depth and 72 dpi. The images in the data set were created from vehicles moving in traffic. Sample images of the data set used in the study are given in Figure 1.



(a) (b) (c) (d)

Figure 1. Sample images in the data set (a) Honda Civic 2015, (b) Suzuki Cary, (c) Kia Sportage, (d) Suzuki Alto 2007

Experiments were coded in Python programming language on the COLAB platform. Analyzes were carried out on the COLAB platform with an Intel(R) Zeon 2.30 GHz processor, 12 GB Ram and Tesla T4 16 GB graphic card.

The images in this dataset were obtained from high-resolution videos collected at different viewing angles and variable frame rates of camera units installed on the highway [4].

3.1 Deep learning

However, thanks to the important developments in recent years, great progress has been made in the field of deep learning. The first was that training deep neural networks became possible as computing power increased. Secondly, the huge amount of data accumulated on the internet could be used for educational purposes. Thirdly, there are innovative developments in optimization algorithms. In this way, deep learning began to show much higher performances than traditional methods in many areas such as image and sound processing and aroused great interest in the field of artificial intelligence [15].

3.2 YOLOv8

YOLO, a deep learning-based object recognition algorithm, was developed by Joseph Redmon and others [16].

YOLO is based on ESA and is used to detect and classify objects on an image. There are many versions of YOLO available, and these versions often come as improved versions of their predecessors. YOLO is used in many applications such as computer vision, image processing, autonomous vehicles, security systems and so on [17].

The main purpose of YOLO is to detect objects in an image and classify these objects into specific classes. The output of YOLO usually includes information such as the predicted label of the object class, the coordinates of the object, and the confidence score.

YOLOv8 is the latest version of the YOLO family of object detection deep learning algorithms based on Convolutional Neural Networks (CNNs) using a similar backbone structure to YOLOv5 from the YOLO(You Only Look Only Once) family. This deep learning algorithm is known for its speed and accuracy in detecting objects in real-time. YOLOv8 outperforms many other object detection algorithms in terms of both speed and accuracy [18].

The main idea of this algorithm is to perform object detection in a single pass through the image, as opposed to running object detection multiple times on different parts of the image as is done in other object detection algorithms. This makes this algorithm fast and efficient in achieving high accuracy when detecting objects. This network is trained on a large image dataset, allowing it to learn patterns and features of real-world objects. Once trained, the network can be used to perform object detection on new images, quickly and accurately detecting the presence and location of objects in the image [19].

As a result, YOLOv8 is a state-of-the-art object detection algorithm that tries to achieve high accuracy due to its fast and high-performance path to detect objects in real time. Its use of a deep neural network and adoption of a single-pass structure for object detection make it an attractive solution for a wide range of applications, including vehicle classification, video surveillance, and more [18].

3.3 Evaluation metrics

After completing the training and testing phases, we measured the performance of our model using accuracy, precision, recall and f1 score.

The mathematical expression of these metrics is given below. In these equations;
TP (true positive): values predicted correctly in the confusion matrix are actually true, FP (false positive): incorrectly predicted values in the confusion matrix are actually correct, FN (false negative): incorrectly predicted values in the confusion matrix are actually incorrect, TN (true negative): values predicted correctly in the confusion matrix are actually incorrect [20, 21]

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 - Score = 2 * \frac{Recall * Precision}{Recall + Precision} \quad (4)$$

A graphical summary of the study is given in Figure 2. First, the images were entered into the system. It was then converted to 640x640 as pre-processing. Pre-processed images are divided into 80% training, 10% validation and 10% testing. It was later classified with YOLOv8. The results obtained are given in Table 3.

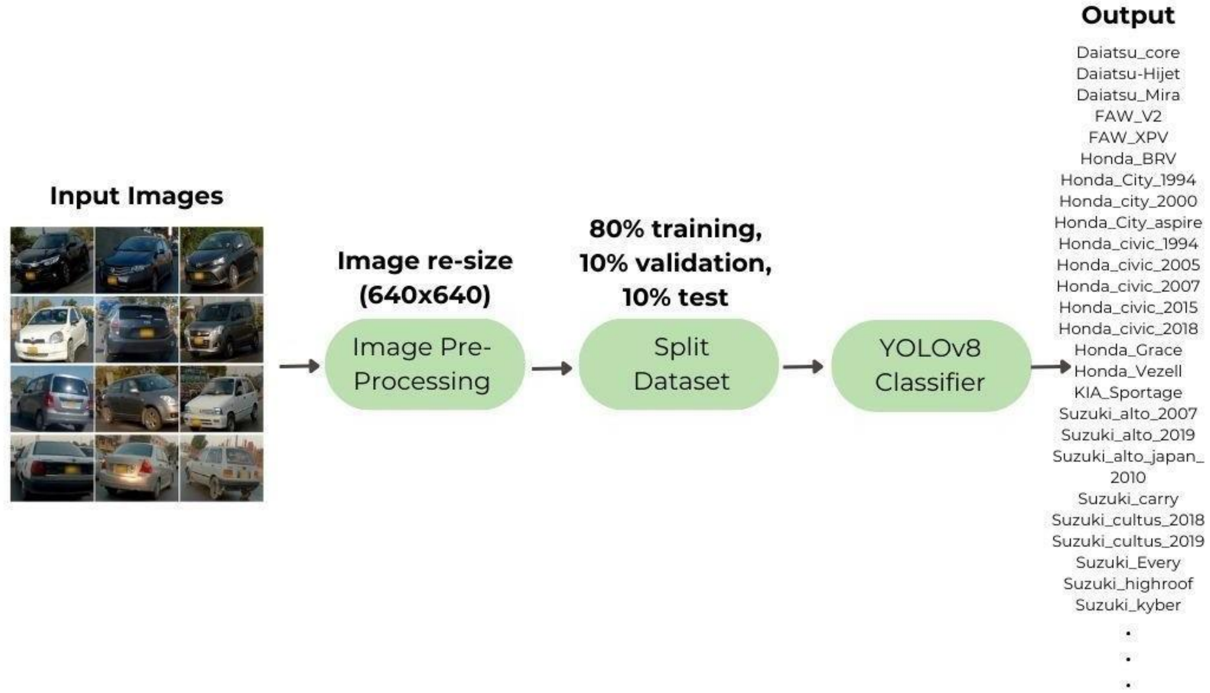


Figure 2. Overview of the study

4. Results and discussion

In this study, 80% training, 10% validation, and 10% testing ratio were used to get the best results from the model. Of the 3847 images, 3079 were used for training, 384 for validation, and 385 for testing. No augmentation process was applied. Image dimensions have been resized to 640x640. Additionally, auto-orientation was applied. Additionally, the parameters used in the classification process with YOLOv8 are given in Table 2.

Table 2. Parameters used for classification in our study on YOLOv8's deep learning model

Accuracy (%)	Precision	Recall	F1-Score
94.28	0.9077	0.9212	0.9063

As a result of classification with YOLO8, accuracy 94.28%, precision 0.9077, recall 0.9212, F1-Score 0.9063 were obtained.

Comparative results of the analyses performed on the 48-class vehicle make and models (VMM) dataset are given in Table 4.

Table 3. Classification studies with deep learning models on VMM dataset

Class	Methods	Accuracy	References
48	ResNet50 ResNet152 MobileNet VGG-16	67.13% 69.24% 73.54% 74.32%	[4]
48	YOLOv8	94.3%	Out Study

In this study, the classification accuracy, which was around 74% for 48 classes, was increased to 94% using YOLOv8. In their study on the same data set, Ali and his colleagues; While we achieved 67.13% classification accuracy with ResNet50, 69.24% with ResNet152, 73.54% with MobilNet, and 74.32% with VGG-16, 94.3% classification accuracy achieved in our study using the YOLOv8 deep learning model.

Graphs showing the training loss, validation loss, accuracy top 1 metrics, and accuracy top 5 metrics values in the analysis made with the YOLOv8 deep learning algorithm are given in Figure 3. These graphics; show that the curves continue regularly. This shows us that the model can be trained consistently and well with the images on this data set.

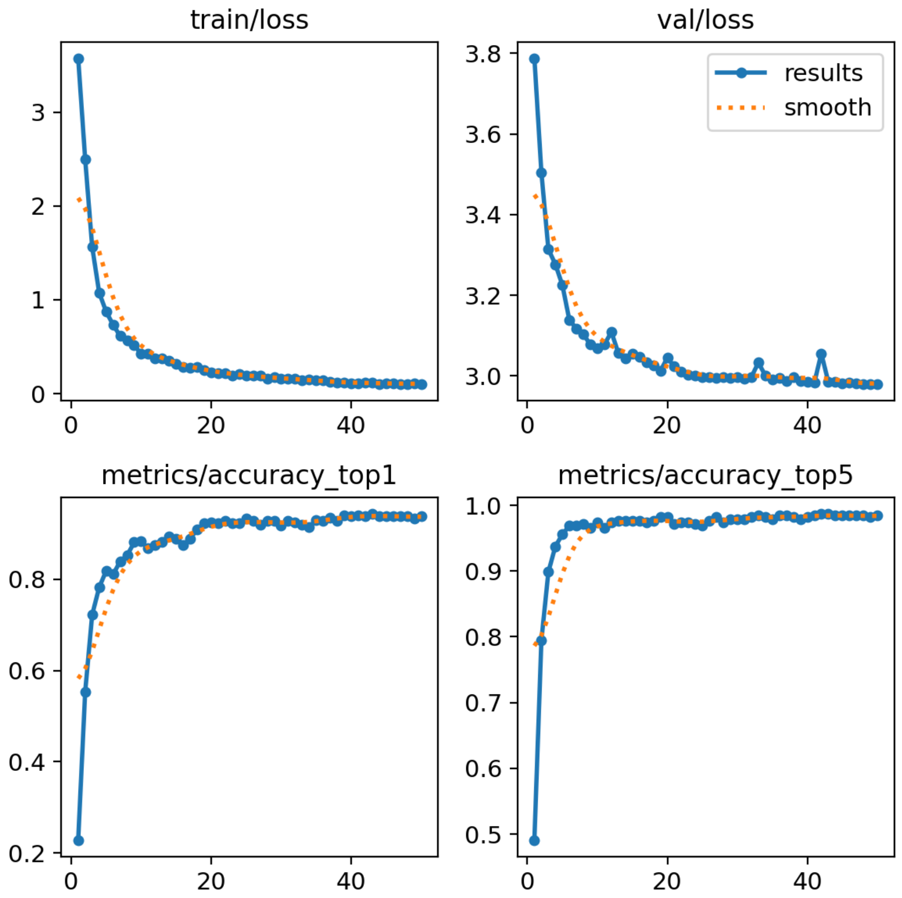


Figure 3. Graphs of train/loss, validation/loss, accuracy top 1 and accuracy top-5

Figure 4 shows the confusion matrix graph in which we classified the images in the data set we used in this study into 48 different vehicle brands and models. It is positioned as predicted in the vertical part of the chart and true in the horizontal part.

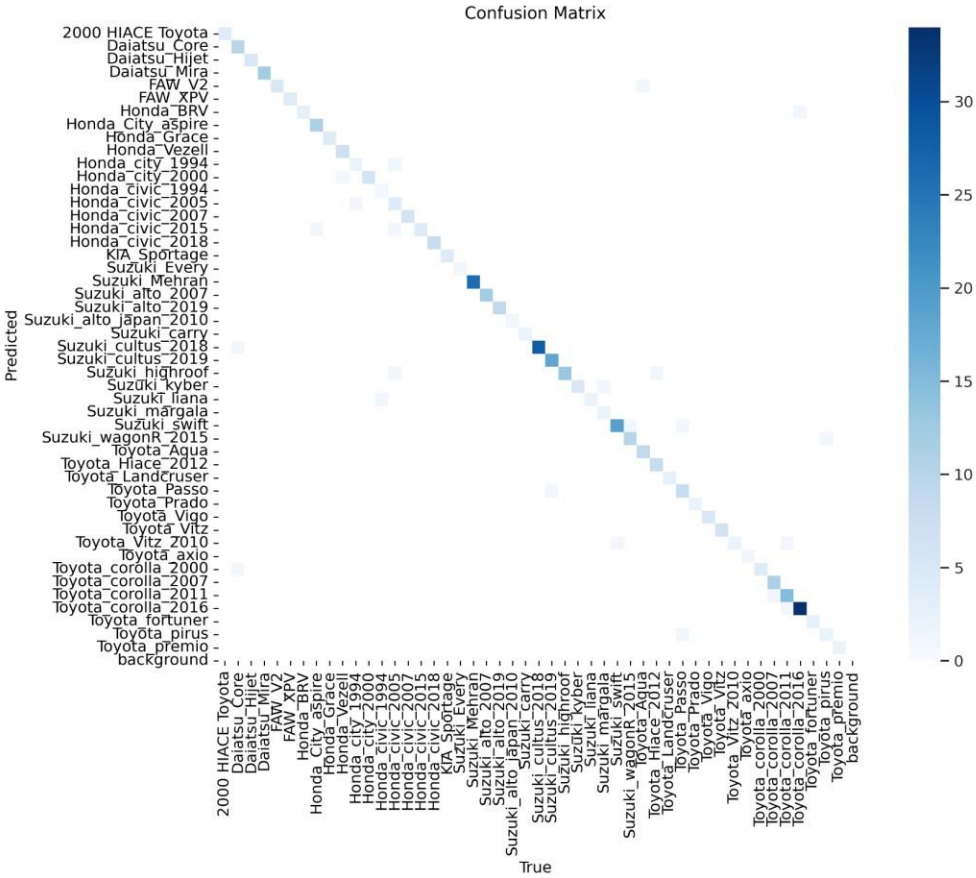


Figure 4. Confusion matrix

The values of the performance metrics resulting from the classification of images of 48 different vehicle models in the data set are given in Table 4.

Table 4. Performance metrics value of classification of 48 different vehicle models images

Class	precision	recall	f1-score	support
2000 HIACE Toyota	1.00	1.00	1.00	3
Daiatsu_Core	1.00	0.82	0.90	11
Daiatsu_Hijet	1.00	0.86	0.92	7
Daiatsu_Mira	0.86	0.86	0.86	7
FAW_V2	1.00	1.00	1.00	2
FAW_XPV	1.00	1.00	1.00	2
Honda_BRV	1.00	1.00	1.00	2
Honda_City_aspire	1.00	0.85	0.92	20
Honda_Grace	1.00	1.00	1.00	2
Honda_Vezell	1.00	1.00	1.00	4
Honda_city_1994	1.00	0.75	0.86	4
Honda_city_2000	1.00	1.00	1.00	7
Honda_civic_1994	0.50	1.00	0.67	1
Honda_civic_2005	1.00	0.80	0.89	5

Honda_civic_2007	1.00	0.92	0.96	13
Honda_civic_2015	0.50	1.00	0.67	2
Honda_civic_2018	0.83	1.00	0.91	5
KIA_Sportage	0.86	1.00	0.92	6
Suzuki_Every	0.67	1.00	0.80	2
Suzuki_Mehran	0.92	0.96	0.94	23
Suzuki_alto_2007	0.87	1.00	0.93	13
Suzuki_alto_2019	1.00	1.00	1.00	6
Suzuki_alto_japan_2010	1.00	1.00	1.00	3
Suzuki_carry	0.00	0.00	0.00	2
Suzuki_cultus_2018	1.00	0.97	0.99	36
Suzuki_cultus_2019	1.00	1.00	1.00	11
Suzuki_highroof	0.78	1.00	0.88	7
Suzuki_kyber	0.83	0.83	0.83	6
Suzuki_liana	1.00	1.00	1.00	2
Suzuki_margala	0.67	0.80	0.73	5
Suzuki_swift	1.00	1.00	1.00	17
Suzuki_wagonR_2015	1.00	1.00	1.00	11
Toyota_Aqua	1.00	0.89	0.94	9
Toyota_Hiace_2012	1.00	1.00	1.00	12
Toyota_Landcruser	1.00	1.00	1.00	2
Toyota_Passo	0.83	0.83	0.83	6
Toyota_Prado	1.00	0.86	0.92	7
Toyota_Vigo	0.86	1.00	0.92	6
Toyota_Vitz	0.92	1.00	0.96	11
Toyota_Vitz_2010	1.00	1.00	1.00	13
Toyota_axio	1.00	0.67	0.80	3
Toyota_corolla_2000	1.00	1.00	1.00	4
Toyota_corolla_2007	0.92	1.00	0.96	11
Toyota_corolla_2011	1.00	0.89	0.94	9
Toyota_corolla_2016	0.97	1.00	0.99	35
Toyota_fortuner	1.00	1.00	1.00	3
Toyota_pirus	0.80	1.00	0.89	4
Toyota_premio	1.00	0.67	0.80	3

Two sample images in the data set, whose classification accuracies were determined as a result of the test, are given in Figure 5.

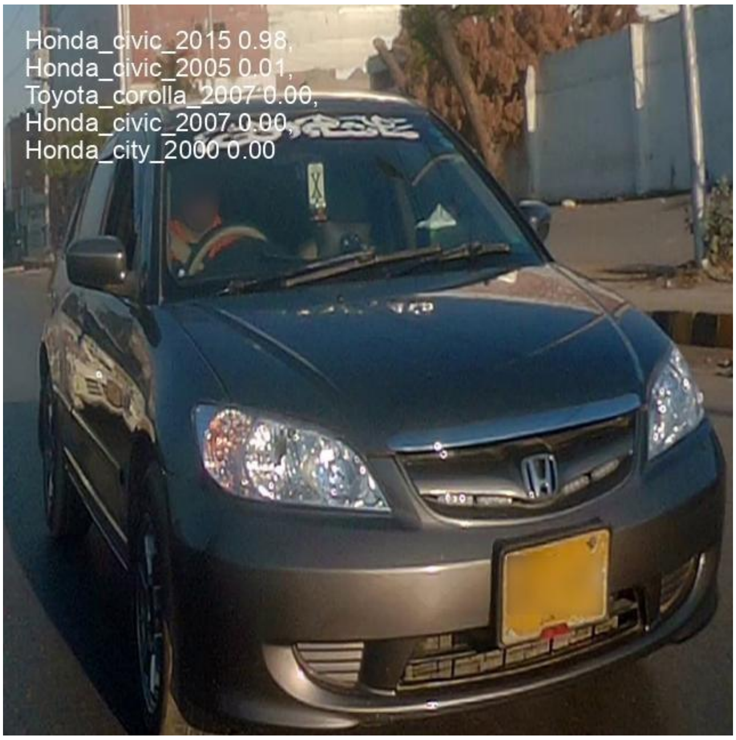


Figure 5. Classification example Honda Civic 2015

5. Conclusion

This study was carried out to evaluate the performance of the YOLOv8-based deep learning model in the task of vehicle brand and model classification. The model was tested on a large data set including various vehicle brands and models, and detailed analysis was provided using various performance metrics. Classification accuracy of 94.28% was achieved.

The results show that the YOLOv8 model has achieved significant success with high accuracy, precision and recall values. The model stands out for its ability to accurately classify various types of vehicles. However, it has been determined that its performance may require further improvement in some special situations and environments where there is not enough light.

In addition, analyzes of the optimal settings of the parameters and hyperparameters used in the training process of the model show that the performance of the model can be further increased. This should be taken into account in future studies to obtain better results and increase the generalization ability of the model.

As a result, the YOLOv8-based deep learning model demonstrated successful performance in vehicle brand and model classification application. Compared to other studies conducted on the same data set, this method significantly increased the classification success. Classification accuracy for the data set used was increased from 74% to 94%. While this study highlights the strengths of the model, it also identifies areas that need potential development for future studies.

In our research, we attained a notable level of classification accuracy through the implementation of YOLOv8, marking a distinct divergence from other studies that have explored the same dataset. Unlike conventional approaches that often leverage a variety of models with varying degrees of success, our decision to utilize YOLOv8 was strategic, aimed at exploiting its advanced capabilities in handling complex image recognition tasks. This choice is a reflection of our study's unique approach, as we sought to harness the latest advancements in deep learning and object detection technologies. The use of YOLOv8 not only underscores our commitment to pushing the boundaries of current methodologies but also highlights the potential for innovative models to significantly enhance classification performance. Our study's differentiation is further underscored by this model choice, positioning it at the forefront of exploring new and efficient ways to achieve high accuracy in classification within our chosen dataset.

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