Vehicle Classification: Using Machine Learning

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Abstract

This paper provides a comprehensive overview of vehicle classification, including its different types, factors that impact it, challenges associated with it, techniques used for it, and its diverse applications. The paper highlights the importance of vehicle classification in transportation planning, traffic management, and vehicle safety systems, and emphasizes the need for continuous research and innovation to overcome the limitations and challenges of vehicle classification.

I. INTRODUCTION

Vehicle detection and classification are crucial in various applications, such as traffic management, surveillance, and autonomous driving. Advances in machine learning and deep learning algorithms have enabled the automatic identification and categorization of different types of vehicles based on their visual features. This process involves collecting images of vehicles from cameras installed in various locations and using machine learning algorithms to analyze the features of the vehicles, such as shape, size, and color. A large dataset of vehicles from different categories is required to train the machine learning model accurately. Once trained, the model can classify new images or video footage of vehicles in real-time. Background subtraction is a common technique for detecting moving objects in a video stream, including vehicles.

However, this technique may not work well in complex environments where the background is dynamic, and lighting conditions change frequently. To overcome these limitations, deep learning approaches, such as Convolutional Neural Networks (CNNs), have been developed. CNNs can automatically learn features from images and classify them accurately, making them useful for vehicle classification. The vehicle detection and classification pipeline involve using background subtraction for detection and CNN for classification. The approach involves pre-processing the video stream to detect moving objects using background subtraction. The resulting foreground mask is then passed to the CNN for classification, where it analyses the features of the detected vehicles and classifies them into different categories.

The accuracy and efficiency of vehicle detection and classification using background subtraction and CNN algorithms depend on the quality of the data and the complexity of the environment. High-quality data is essential to overcome the limitations and errors in the classification process. In complex environments where the background is dynamic, CNNs can provide better performance than traditional methods. Therefore, the use of CNNs for vehicle classification has become increasingly popular in recent years.

II. LITERATURE REVIEW

The use of machine learning techniques for vehicle classification has been a topic of active research in recent years. This literature review provides an overview of 13 relevant papers that explore various aspects of vehicle classification and image classification using machine learning algorithms.

Several papers focus on providing comprehensive reviews of recent research in vehicle classification using deep learning. Alattas et al. (2020) and Kim and Park (2021) provide a review and a systematic review, respectively, comparing and analyzing different approaches and outlining potential directions for future research. Alamri et al. (2021) and Alshawi and Lim (2021) also provide systematic reviews of vehicle classification using machine learning techniques, discussing the advantages and limitations of each method. Ghosh et al. (2021) and Krizhevsky et al. (2017) provide comprehensive surveys of deep learning techniques for image classification, discussing the evolution of deep learning methods and their impact on image classification, effectiveness on a real-world dataset and comparing it with other state-of-the-art techniques. Chen et al. (2021) propose a vehicle classification method based on a CNN and image segmentation, also demonstrating its effectiveness on a real-world dataset and comparing it with other state-of-the-art techniques. Fan et al. (2019) propose a method for vehicle type classification using low-resolution images and machine learning techniques, demonstrating its effectiveness on a real-world dataset. Bouwmans et al. (2018) provide a survey of background subtraction techniques for vision-based intelligent systems, discussing the challenges and limitations of existing methods and providing an overview of the latest techniques for background subtraction.

Overall, the reviewed papers highlight the challenges and limitations of existing methods for vehicle classification and image classification using machine learning techniques. However, they also demonstrate the effectiveness of deep learning techniques, particularly CNNs, for these tasks. Additionally, the papers provide insights into the advantages and limitations of different approaches.

III. METHODOLOGY

The proposed methodology uses machine learning or deep learning techniques. The implementation process involves the following steps:

1. Data collection: Collect data from sources like open-source repositories, web scraping, or data providers.

2. Data pre-processing: Cleaning the collected data to remove unwanted images, not proper visible images and other irrelevant information.

3. Data Labelling: Labelling the data and classifying them under their respective classes like bicycle, bus, car and motorcycle.

4. Model training: Training a machine learning or deep learning model on the labelled data and extracted features to predict the class of new vehicle data.

5. Model evaluation: Evaluating the performance of the model using and propose potential directions for future research. various metrics such as accuracy, precision, recall, or F1-score.

6. Deployment: Deploying the model in the production environment to classify the
4 major classes of vehicle

A. Data Collection

The collection of the dataset from various sources like open-source repositories, web scraping, or data providers. The dataset contains 4 classes of the vehicles with their respective labels. In all class respective images are present. The total number of images in all the classes is approximately 13518. Now this needs to be pre-processed for smooth train and testing.

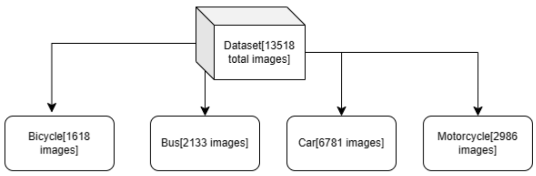

Figure 1 Dataset

B. Data-Pre-processing

Pre-processing is a crucial step in building deep learning models for image classification tasks. It involves preparing the image data and their corresponding labels in a format that can be used for training a deep learning model. It shuffles a list of image file paths and then reads and resizes each image using OpenCV's functions. For each image in the shuffled list, it reads the image using OpenCV's imread function and resizes it to a fixed size of 64 by 64 pixels using OpenCV's resize function. The image data is stored in a list for further processing. Moreover, the it extracts the label of each image from its file path using the split function and creates a one-hot encoded vector using NumPy. This is a standard approach for classifying images in deep learning models. The one-hot encoded label is stored in a separate list for further processing.

Splitting of Data

For this study the dataset is split into train set and test set in **75:25** ratio. The train set is used to train the deep learning CNN model, while test set is used to evaluate how well our model performs.

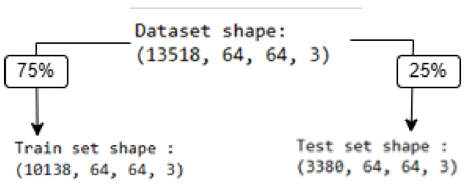

Figure 2 Splitting of Data

C. Model Selection and Model specifications:

There are several machine learning algorithms available for multi-class classification, such as Support Vector Machines (SVM), Random Forest, and Convolutional Neural Networks (CNN). For this task, a CNN model may be the best choice since it can capture the visual features of vehicles and identify patterns in the images. The methods that are going to use involve deep learning techniques, specifically Convolutional Neural Networks (CNNs), which are highly effective for image classification and object. Using Python for implementing these methods allows for a flexible and user-friendly programming environment, with access to a rich set of machine learning libraries and frameworks. Additionally, CNNs offer advantages such as automatic feature extraction, which can greatly improve the accuracy of classification tasks, and the ability to handle large amounts of data with relatively few parameters. Overall, the combination of Python and CNNs provides a powerful toolset for solving complex image processing problems.

D. Preparing Model

The convolutional neural network (CNN) model is using the Keras API with TensorFlow as its backend. The CNN model is designed to classify images into four categories based on the labels assigned. The model architecture consists of several convolutional layers with varying filter sizes, pooling layers to reduce the dimensionality of the output, and densely connected layers with rectified linear unit (ReLU) activation functions. The CNN model uses the softmax activation function in its output layer to classify the input image into one of four categories. The code also includes dropout layers, which randomly drops out some neurons during training to prevent overfitting, and regularization techniques such as L2 regularization to reduce the impact of overfitting. The model is compiled using the categorical cross-entropy loss function and stochastic gradient descent (SGD) optimizer with a learning rate of 0.001. The metrics used to evaluate the model's performance are accuracy and loss.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 64, 64, 64)	1792
conv2d_1 (Conv2D)	(None, 64, 64, 128)	73856
conv2d_2 (Conv2D)	(None, 64, 64, 64)	73792
max_pooling2d (MaxPooling2D)	(None, 21, 21, 64)	0
flatten (Flatten)	(None, 28224)	0
dropout (Dropout)	(None, 28224)	0
dense (Dense)	(None, 750)	21168750
dense_1 (Dense)	(None, 750)	563250
dropout_1 (Dropout)	(None, 750)	0
dense_2 (Dense)	(None, 600)	450600
dense_3 (Dense)	(None, 600)	360600
dropout_2 (Dropout)	(None, 600)	0
dense_4 (Dense)	(None, 500)	300500
dense_5 (Dense)	(None, 500)	250500
dense_6 (Dense)	(None, 4)	2004

Total params: 23,245,644
Trainable params: 23,245,644
Non-trainable params: 0

Figure 3 : Model Summary

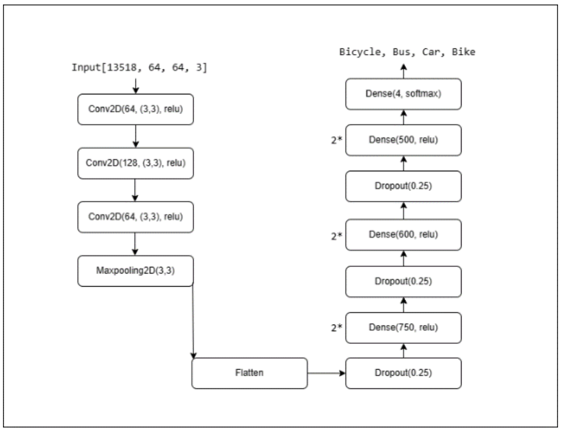

Figure 4: Layers of CNN

E. Model Evaluation

The training accuracy is **96%** while the test accuracy is **80.7%.**

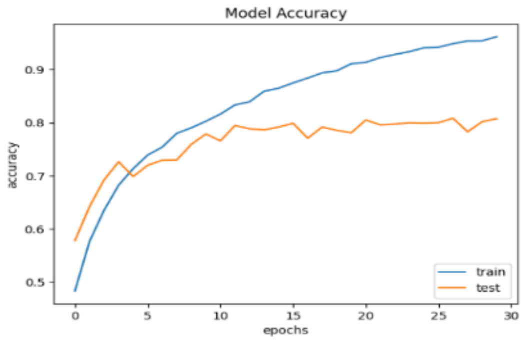

Figure 5 : Model Accuracy

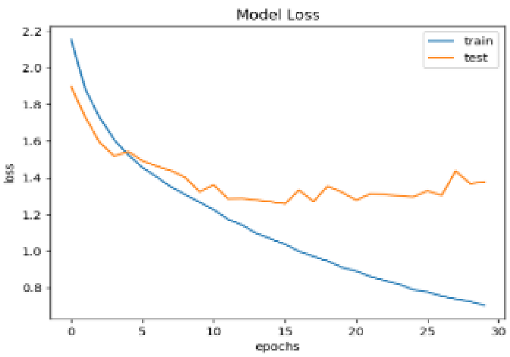

Figure 6 : Model Loss

Here is the classification report of this model consisting of accuracy, precision, recall, or F1-score of all the classes as well. Labels 0,1,2 and 3 denotes Bicycle, Bus, Car and Motorcycle respectively.

```
matrix = classification_report(actual,predicted,labels=[0,1,2,3])
print("Classification Report : \n", matrix)
```

```
Classification Report :
              precision    recall  f1-score   support

           0       0.88      0.91      0.90      1618
           1       0.95      0.97      0.96      2133
           2       0.97      0.96      0.97      6781
           3       0.92      0.92      0.92      2986

    accuracy                           0.95     13518
   macro avg       0.93      0.94      0.94     13518
weighted avg       0.95      0.95      0.95     13518
```

Figure 7 : Classification Report

F. Limitations

Vehicle classification systems are not without limitations. They can be subjective, leading to inconsistencies in classification due to different criteria used. Ambiguity can arise when a vehicle does not fit neatly into a single category. While vehicle classification systems can be useful for organizing and managing vehicle data, these limitations should be considered and approached with caution.

Here are few:

1. Limited Classes: The model consists of only 4 classes as of now, and the vehicles are only of road transportation.
2. Complexity: Some classification systems may be complex and difficult to understand, which can lead to errors in classification.
3. Lack of flexibility: Classification systems may not be flexible enough to accommodate changes in technology and new types of vehicles.
4. Cost: Implementing a vehicle classification system can be costly, and the cost may not always be justified by the benefits.
5. Only road transportation: As of now the model can only be working upon the vehicle present in roadways.

IV. CONCLUSION

In conclusion, vehicle detection and classification using machine learning algorithms and deep learning approaches has the potential to revolutionize various industries, including transportation and surveillance. The combination of techniques such as Convolutional Neural Networks (CNNs) can provide accurate and efficient results. However, there are still challenges that need to be addressed, such as the need for high-quality data and the limitations of traditional methods in complex environments. Further research is required to develop more robust and reliable algorithms that can provide accurate results in different environmental conditions. Despite these challenges, the benefits of using machine learning for vehicle detection and classification are significant. In transportation, it can help optimise various industries.

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