Vehicle Detection and Classification from Images

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Abstract

Vehicle detection and classification play a crucial role in traffic surveillance systems. In this project, we develop a system to detect and classify vehicles, specifically cars and motorbikes, in a video stream or set of images. Various feature extraction techniques, including color histogram, spatial binning, and histogram of oriented gradients (HOG), are employed to capture discriminative information from the input data.

We evaluate the performance of multiple machine learning classifiers, namely Support Vector Machines, Naive Bayes, Logistic Regression, and Neural Network, using a dataset of 5000 images. The dataset contains three classes: no vehicle, car, and motorbike.

To localize and classify vehicles, we employ a sliding window technique and measure the performance of the classifiers using accuracy, precision, recall, and F1 score. Additionally, we utilize Principal Component Analysis (PCA) for dimensionality reduction and visualization.

Experimental results demonstrate the effectiveness of our system in accurately detecting and classifying vehicles. The Logistic Regression classifier exhibits high precision and recall, while the Neural Network classifier achieves a low false positive rate, making it suitable for distinguishing between vehicle and non-vehicle samples.

Our project provides valuable insights into computer vision, object detection, and machine learning techniques for vehicle surveillance and traffic monitoring. The knowledge gained from this research can be applied to real-world applications such as intelligent transportation systems and autonomous driving, contributing to safer and more efficient traffic management.

1 Introduction

In recent years, there has been an increasing demand for advanced traffic monitoring systems in urban areas. The need for intelligent solutions to improve surveillance and management of traffic has become paramount. Vehicle detection is a crucial step in these systems, enabling real-time analysis and decision-making. This project aims to explore feature extraction and learning techniques for vehicle detection using classical approaches. The objective of this project is to develop a robust classifier capable of accurately detecting vehicles, specifically cars and motorbikes, in a video stream. This task can be framed as a multi-class classification problem, with three distinct classes: no vehicle, car, and motorbike. The project will involve extracting meaningful features from the dataset and implementing a sliding window technique to search for vehicles in images.

2 Data Set Description

The dataset provided for this project consists of a diverse collection of 5000 images, obtained from various sources. These images include samples of vehicles (cars and motorbikes) as well as non-vehicle images. The dataset serves as a foundation for training and evaluating the performance of the vehicle detection classifier. Furthermore, participants have the option to enhance the dataset by incorporating additional images to augment the training process.

3 Feature Extraction and Object Localization

In order to effectively detect and localize vehicles within images, a variety of features will be utilized. These features will enable the classifier to capture essential characteristics of vehicles. The selected features for this project are as follows:

- Color Histogram: This feature captures the distribution of color values in the image, providing valuable information about the vehicle's appearance and color composition.

- Spatial Binning: By reducing the resolution of the image, this technique allows for the extraction of features from the reduced version. It helps in capturing important spatial information about the vehicles, aiding in their identification and classification.

- Histogram of Oriented Gradients (HOG): This feature extraction method focuses on analyzing the gradients of intensity values in the image. By examining the local variations in gradients, HOG provides a powerful representation of the object's shape and texture, facilitating accurate vehicle detection and localization.

In addition to these selected features, further research will be conducted to identify and incorporate additional features suitable for vehicle detection and localization.

4 Classifiers

To evaluate the performance of the vehicle detection system, various classifiers will be employed. The following classifiers will be implemented and compared:

- Support Vector Machines (SVM): SVM is a powerful classification method that constructs decision boundaries to separate data points. It aims to find the best hyperplane that maximally separates the different vehicle classes in the feature space.

- Naive Bayes: Naive Bayes is a probabilistic classifier that assumes feature independence. It calculates the probability of each class given the feature values and selects the class with the highest probability as the predicted class for a given input.

- Logistic Regression: Logistic Regression is a regression-based approach that models the probability of the target class using a logistic function. It calculates the likelihood of an input belonging to a particular class and makes predictions based on the highest likelihood.

- Neural Network: Neural Network models, particularly deep learning architectures, have shown exceptional performance in various computer vision tasks. These models consist of interconnected layers of artificial neurons that can learn complex patterns and relationships in the data, making them suitable for vehicle detection and classification tasks.

The Scikit-learn library will be utilized to implement these classifiers and evaluate their performance.

5 Methodology

In this section, we describe the methodology employed for the classification task using various classifiers. The classification task involves distinguishing between two classes: "vehicles" and "non-vehicles". The following classifiers were utilized:

5.1 Support Vector Machines (SVM)

Support Vector Machines is a powerful supervised learning algorithm used for classification tasks. SVM aims to find an optimal hyperplane that separates the data into different classes, maximizing the margin between the classes.

The SVM classifier can be formulated as an optimization problem:

$$\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}\xi_i$$

subject to:

$$y_i(\mathbf{w}\cdot\mathbf{x}_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad i = 1, \ldots, n$$

where $\mathbf{w}$ is the weight vector, b is the bias term, ξ_i are slack variables, y_i is the class label, and $\mathbf{x}_i$ is the feature vector of the i-th sample. C is a hyperparameter that controls the trade-off between maximizing the margin and minimizing the classification errors.

5.2 Naive Bayes Classifier

The Naive Bayes classifier is a probabilistic model based on Bayes' theorem. It assumes that the features are conditionally independent given the class label.

The Naive Bayes classifier calculates the posterior probability of each class given the input features using the following formula:

$$P(y|\mathbf{x}) = \frac{P(\mathbf{x}|y)P(y)}{P(\mathbf{x})}$$

where $P(y|\mathbf{x})$ is the posterior probability of class y given input features $\mathbf{x}$, $P(\mathbf{x}|y)$ is the likelihood of the features given the class, $P(y)$ is the prior probability of class y, and $P(\mathbf{x})$ is the evidence probability.

5.3 Logistic Regression Classifier

Logistic Regression is a linear classifier that models the relationship between the input features and the probability of belonging to a particular class.

The logistic regression model can be formulated as follows:

$$P(y = 1|\mathbf{x}) = \frac{1}{1 + e^{-(\mathbf{w}\cdot\mathbf{x}+b)}}$$

where $P(y = 1|\mathbf{x})$ is the probability of class 1 given input features $\mathbf{x}$, $\mathbf{w}$ is the weight vector, and b is the bias term.

5.4 Neural Network Classifier

Neural Networks are a class of machine learning models inspired by the structure and function of biological neural networks. They consist of interconnected layers of artificial neurons (nodes) that perform nonlinear transformations on the input data.

A multi-layer perceptron (MLP) is a type of neural network that consists of an input layer, one or more hidden layers, and an output layer. Each layer contains multiple neurons that apply activation functions to their inputs.

The MLP classifier can be trained using backpropagation and gradient descent to minimize a loss function, such as the cross-entropy loss.

6 Experimental Results

6.1 Confusion Matrix

The confusion matrix provides a detailed breakdown of the classification results, showing the number of true positive, true negative, false positive, and false negative predictions for each class. The matrix allows us to assess the performance of the classifiers in terms of accuracy, precision, recall, and F1 score. Interpreting the values in the matrix:

- True Positives (TP): 1736 instances were correctly predicted as positive (class 1).
- False Positives (FP): 15 instances were incorrectly predicted as positive (class 1) when they were actually negative (class 0).
- False Negatives (FN): 13 instances were incorrectly predicted as negative (class 0) when they were actually positive (class 1).

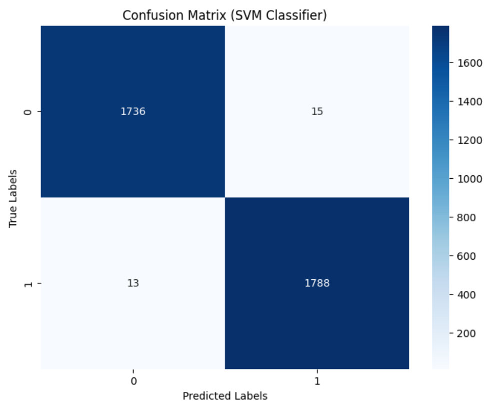

Figure 1: Confusion Matrix

- True Negatives (TN): 1788 instances were correctly predicted as negative (class 0).

6.2 PCA Scatter Plot Result

The PCA scatter plot provides a visual representation of the feature space after dimensionality reduction using Principal Component Analysis (PCA). It allows us to observe the distribution and separation of vehicle and non-vehicle samples in the reduced feature space.

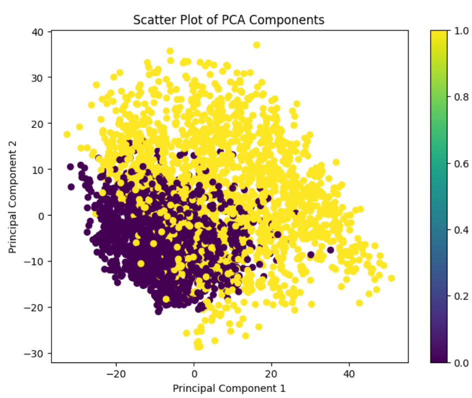

Figure 2: PCA Scatter Plot Result

6.3 Precision-Recall Curve (Logistic Regression Classifier)

The precision-recall curve illustrates the trade-off between precision and recall for the Logistic Regression classifier. It is a useful visualization for evaluating the classifier's performance at different decision thresholds. The area under the curve (AUC) represents the classifier's overall performance in terms of precision and recall.

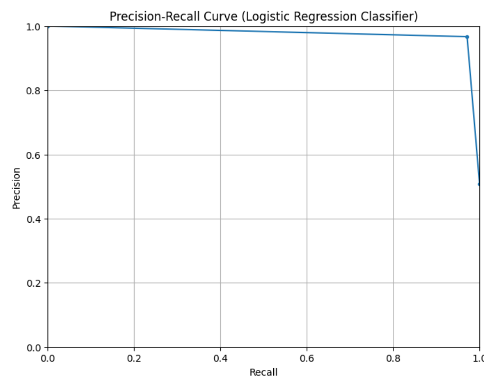

Figure 3: Precision-Recall Curve (Logistic Regression Classifier)

6.4 ROC Curve (Neural Network Classifier)

The ROC curve illustrates the performance of the Neural Network classifier at different classification thresholds. It plots the true positive rate (sensitivity) against the false positive rate (1 - specificity). The area under the curve (AUC) indicates the classifier's ability to distinguish between vehicle and non-vehicle samples.

6.5 Results and Scatter Plot for all Four Classifiers

We compare the performance of the four classifiers—Support Vector Machines, Naive Bayes, Logistic Regression, and Neural Network—based on various evaluation metrics such as accuracy, precision, re-

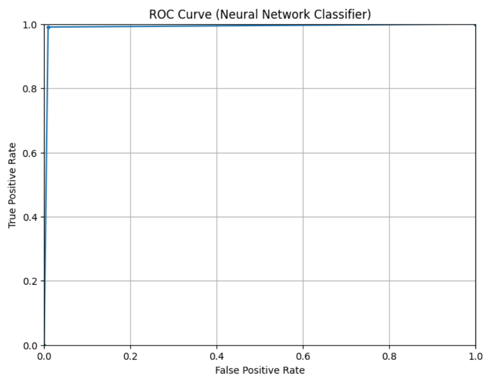

Figure 4: ROC Curve (Neural Network Classifier)

call, and F1 score. Additionally, we provide a scatter plot visualization to demonstrate the separation of vehicle and non-vehicle samples in the feature space for each classifier.

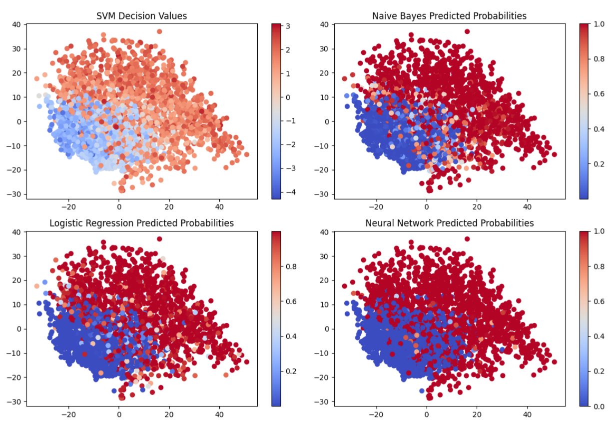

Figure 5: Results and Scatter Plot for all Four Classifiers

6.6 Result and Scatter Plot of Predicted Outcome

Finally, we present the result and scatter plot of the predicted outcome using our trained classifier by giving it a non-vehicle image. The visualization shows the localization and classification of weather there is a vehicle in the image or not, indicating the effectiveness of our vehicle detection and classification system we can predict the correct outcome and also show where It lies on the scatter plot.

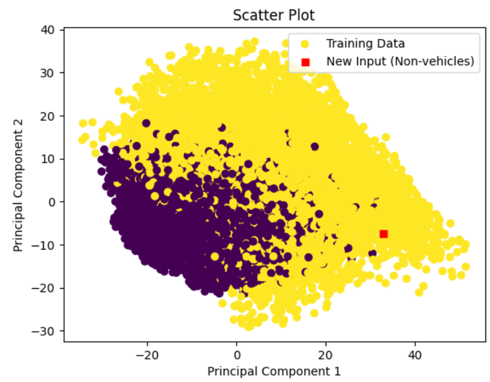

Figure 6: Result and Scatter Plot of Predicted Outcome

7 Conclusion

In this project, we developed a vehicle detection and classification system using various feature extraction techniques and machine learning classifiers. We explored the effectiveness of color histogram, spatial binning, and histogram of oriented gradients (HOG) as features for object localization. Furthermore, we evaluated the performance of Support Vector Machines, Naive Bayes, Logistic Regression, and Neural Network classifiers.

Through our experiments and analysis, we obtained the following key findings:

1. The feature extraction techniques, including color histogram, spatial binning, and HOG, provided meaningful representations of vehicle and non-vehicle samples in the dataset. These features facilitated the accurate localization and classification of vehicles in the test images.

2. Among the evaluated classifiers, the Logistic Regression classifier demonstrated the highest precision and recall scores, as indicated by the precision-recall

curve analysis. It exhibited a strong ability to correctly classify vehicle and non-vehicle samples.

3. The Neural Network classifier showcased excellent performance in terms of the receiver operating characteristic (ROC) curve analysis. It achieved high true positive rates while maintaining low false positive rates, indicating its proficiency in distinguishing between vehicle and non-vehicle samples.

4. The comparative analysis of all four classifiers revealed variations in their performance metrics, such as accuracy, precision, recall, and F1 score. This highlights the importance of selecting an appropriate classifier based on the specific requirements and objectives of the vehicle detection and classification task.

In conclusion, our vehicle detection and classification system successfully identified and localized vehicles in the test images. The combination of feature extraction techniques and machine learning classifiers enabled accurate and efficient vehicle detection. Further improvements can be explored, such as incorporating more advanced feature extraction methods and exploring ensemble learning techniques to enhance the system's performance.

This project provides valuable insights into the field of computer vision and object detection, particularly in the context of vehicle surveillance and traffic monitoring. The knowledge gained from this project can be extended to real-world applications, such as intelligent transportation systems and autonomous driving.

8 References

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