Performance Comparison of the Best SVM Kernel: With and Without Feature Engineering for Vehicle Detection

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***Abstract*—This paper presents the development of an automated vehicle classification system using machine learning techniques, specifically Support Vector Machine (SVM). To enhance classification accuracy, Histogram of Oriented Gradients (HOG) was applied as a feature engineering method. The study compares the performance of a baseline model, which uses only grayscale and resized images, to a modified SVM model utilizing HOG features. Results indicate a significant improvement in accuracy, with the modified SVM achieving an accuracy rate of 82.50%, compared to 56.25% for the baseline model. These findings demonstrate the effectiveness of feature engineering in vehicle classification tasks. Future work includes exploring additional machine learning models, expanding datasets, and developing new feature extraction techniques to further improve model accuracy and support practical applications in traffic management and law enforcement.**

***Index Terms*—machine learning, vehicle classification, Support Vector Machine (SVM), feature engineering, Histogram of Oriented Gradients (HOG), traffic management, law enforcement.**

I. Introduction

Vehicles have significantly transformed the way of a life, from transportation, trade, and personal usage. With the demand for the usage of vehicles continues to grow, challenges arises such as the handling of traffic and identification of each vehicle that offends the law. Technology, at the same time provides a crucial impact on people, offering tools that could make tasks more efficient.

While humans can easily recognize vehicles in videos or images or to identify different types of cars. In computer algorithms and programs it is highly depend on the types of data Some challenges like the weather or light are also plays important role on making the process easy or much hard. At the same time we have different types and shapes of vehicles [1] which makes recognition more complex.

With the rapid growth of the economy and the fast development of technology, artificial intelligence (AI) has been widely applied in various domains [3] such as vehicle model recognition and number plate recognition systems. This design presents an effective and robust frame for automatic vehicle model identification and number plate birth from images or videotape streams [2]. AI's core foundation, Machine Learning (ML) is composed of complex of algorithms and methods that address the problems of classification, clustering, and forecasting [4]. There is a wide range of machine learning algorithm models to use when it comes to solving different issues. Different models may have different advantages and disadvantages in terms of performance, complexity, and interpretability. Using an unsuitable model may lead to low accuracy, high computational cost, poor generalization, or other negative consequences [6].

Currently, vehicle detection suffers from low performance in terms of accuracy and time costs in real-time application [5]. This study aims to analyze Support Vector Machine (SVM) and to compare the impact of feature engineering on improving the accuracy rate and efficiency of the model. This solution provides understanding the comparison of SVM with and without feature engineering and will support traffic management on cities and the law enforcers once applied to real world systems.

II. Review of Related Literature

A. *Overview of key concepts and background information*

Support Vector Machines (SVM) plays a vital role in vehicle type recognition due to its effectiveness on classification. SVMs are part of machine learning tools that are used also in regression analysis. Learning algorithms associated with SVMs are supervised learning models that recognize pattern by analyzing the data. The effectiveness of SVM is achieved mostly when used with Feature Extraction techniques such as Histogram of Oriented Gradients (HOG) that allows the machine to capture details from the image even in complex or changing environments. Although Convolutional Neural Network (CNN) is mostly known when it comes to leading algorithms for image processing, this Deep Learning algorithm is known for the usage on three - dimensional data for classification and object recognition tasks. SVMs still offers a balanced solution between the performance and efficiency even with limited data and computational resources.

B. Review of other relevant research papers

Focusing on vehicle detection using SVM and HOG kernels or feature engineering, a related study entitled "Improving Vehicle Detection by Adapting Parameters of HOG and Kernel Functions of SVM" is relevant on the study being conducted. It illustrates effective strategies for improving the accuracy of the SVM model with experimenting different kernels and optimizing each with HOG. The related study shows how parameter tuning could enhance the performance detection. The findings mentioned by the researchers with the processes done shows the importance of tailored feature extraction and parameter adaptation in machine learning algorithms.

Highlighting the practical benefits of parameter tuning, the relevance of this information to the study to be conducted provides considerations on using similar optimizations. While the related study provides a general approach on usage of SVM kernels, the study to be conducted will specifically be focusing on a single SVM kernel, providing a more targeted investigation into it's effectiveness in vehicle type recognitions.

C. Current State of Art

Currently, the state of art in the field of vehicle type recognition is influenced by both machine and non - machine learning models. One of the best known available algorithm is Convolutional Neural Networks (CNNs), a deep learning algorithm where compared to traditional methods, it can automatically learn feature representations in images without the need for manual feature design. This allows capture of information contained in images better [9]. Advantage of CNNs is that it is highly effective for image processing for it can learn hierarchical features which allows it to achieve high accuracy on vehicle detection tasks even with complex environments. A limitation present in CNNs is that the challenge of implementing on real - time applications for rapid processing is crucial.

In addition, Support vector machine (SVM) is a commonly used machine learning algorithm that learns the boundary between labeled sample data of target objects and background. This algorithm can be applied to detect new objects in images. Through algorithm training, machine learning algorithms can automatically learn the features and classification patterns of target objects, there by enhancing the accuracy and robustness. Being able to offer binary classification and robust performance with limited computational resources makes the model an advantage for practical real - time vehicle type detection which makes it straightforward for classification tasks. Once combined to feature engineering techniques, SVMs can achieve a reliable detection in scenarios providing lower data points and lower computational power requirements. However, a disadvantage of SVM is that it doesn't perform well on complex multi-type recognition tasks.

Vehicle detection model performance is commonly assessed with widely accepted benchmarks, metrics such as Intersection over Union (IoU), precision (P), recall (R), F1-score, Average Precision (AP), and mean Average Precision (mAP) are commonly utilized to evaluate detection accuracy of algorithms [10]. These are essential for evaluating and comparing the accuracy and effectiveness of different models or kernels.

D. Prior Attempts to Solve the Same Problem

Several researchers and companies have attempted to solve the problem of vehicle type recognition through various approaches. The work by Laopracha et al. (2014), as mentioned earlier, focused on optimizing SVM with HOG for vehicle detection, achieving improved accuracy through parameter tuning. Their success demonstrated the importance of tailored feature extraction in enhancing machine learning model performance. However, their approach was general, without delving into the potential advantages of a single optimized SVM kernel for targeted tasks.

By contrast, the current study seeks to build upon these findings by focusing on a specific SVM kernel, aiming to provide a more focused investigation into its applicability for vehicle type recognition. This approach is intended to address some of the limitations in previous studies, particularly in achieving reliable, real-time detection with minimal computational resources.

III. METHODOLOGY

The dataset used for this research consists of a collection of well-organized and labeled vehicle images. Containing folders separated thru it's vehicle types. The study focuses on SVM as the primary machine learning algorithm. On facilitating the training and testing of datasets, certain Python libraries were used to provide efficient analysis on vehicle classifications. The methodology is structured into distinct sections to provide a more detailed discussion on the techniques and processes used through the research.

A. Data Collection

The dataset used in this study is retrieved from Kaggle and is specifically made for vehicle type recognition.The dataset consists a collection of a hundred images organized into folder according to their vehicle type which are cars, trucks, buses, and motorcycles. Each image is labeled into it's specific vehicle type for easy identification.

The data was collected and compiled by Kaggle users and is made available for the public for research and project developments. The images collected were from various sources to ensure the distinctiveness of the vehicles on types and different environment scenarios.

B. Data Pre-Processing

In preparing of the dataset for vehicle type recognition, several pre-processing steps were done to ensure data and model efficiency. Since the dataset doesn't contain any empty values, there were no handling of missing values performed in this dataset. As the dataset is composed of images, each was resized into a dimension of 100x100 pixels for uniformity of it's sizes and then converted to grayscale, to simplify and focus on the essential features of the data.

The study conducted is a comparative type wherein a two approaches were done, one is without any feature engineering to show the baseline performance of the model, and the other with feature engineering modifications to improve the accuracy.

Feature Engineering was done for enhancing the accuracy of the model, Histogram of Oriented Gradients (HOG) was applied to capture the key details in each image. The HOG function extracts the shape and texture features from the image where the size of each cell within the image becomes 16x16 pixels. On the other hand, the block structure became a 2x2 arrangement of cells. This helps normalizing the gradient information within the cells.

C. Experimental Setup

In this study, the tools and frameworks used include Python as the main programming language together with its libraries such as OpenCV with a version of 4.5.3 for image processing, NumPy for numerical operations, and sci-kit with a version of 1.0.2 learn for the implementation of the SVM model. The experimentation of datasets were done with a laptop equipped with a Graphics Processing Unit (GPU) for acceleration of the computations involved when it comes to image processing and training of the model.

The dataset were organized into two sets, the training and test subsets, where 80% were allocated for the training the model and 20% for testing the performance. With the help of the train_test_split function, the splitting of the data was achieved.

In the first approach, there were no feature engineering done which implements the baseline model by using the Radial Basis Function (RBF) kernel of SVM.

On the other hand, the second approach uses feature engineering which is the HOG where it extracted features from images to enhance the model's performance.

Hyperparameters in the SVM model was initialized with a regularization parameter C which is set to 1.0 for the modified approach. HOG parameters which are pixels_per_cell (16,16) and cells_per_block (2,2) were set to ensure the effectiveness of the representation of the image features while maintaining the balance of performance and computational efficiency.

D. Algorithm

The algorithm used in the study is Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel on classifying vehicle images. SVM is chosen as an algorithm for its strong performance in tasks involving image classifications. The RBF kernel is used for it suits the task due to its ability to handle complex patterns in high-dimensional area and when it shows a promising accuracy rate among the other SVM kernels.

Two approaches of SVM algorithm were done, first is the without feature engineering and a modified version where it uses feature engineering. Initially, the images were resized and converted to grayscale, then flattened. This provides a uniformed dataset for training while preserving the essential details of the vehicles.

The second approach used HOG to capture important edges and gradient directions in the image database, providing a more descriptive feature for the model to support. This feature allows the aimed dataset to improve and achieve a good result of accuracy rate.

Focusing on the dataset and its model, the sets are divided into training and test following an 80% and 20% split. To balance the model's generalization C is set to 1.0 to balance the model's generalization and accuracy for providing a better result on vehicle classification.

E. Training Procedure

In training the algorithm the dataset was first split in 80:20 ratio. Then 80% of the two sets were combined and used a training data of the classifier while the remaining 20% as testing data. Overall, the training data consists of 320 pictures, wherein 80 photos for each classification - 'Bus', 'Car', 'Motorcycle', 'Truck' are labeled as is. On the other hand, the testing data consists of 80 pictures where in 20 are pictures are labeled for each classification - 'Bus', 'Car', 'Motorcycle', 'Truck'.

SVM with an RBF kernel was chosen for this problem due to their effectiveness in handling non liner classification problems. The RBF kernel works best in scenarios where the data is non linearly separable. Support Vector Machine (SVM) is a supervised machine learning algorithm used for classifications tasks. It works by finding the hyperplane that best separates the data points of different classes in high-dimensional space.

To enhance the accuracy and efficiency of the model, Histogram of Oriented Gradients (HOG) was employed as the primary feature extraction technique. This method captures essential details by focusing on the shape and texture of the images. Each image in the dataset was first resized to 100x100 pixels for uniformity and then converted to grayscale to simplify the data and highlight critical features. The HOG function was applied to these preprocessed images, extracting important edge and gradient direction information. The parameters for HOG were set with pixels per cell as 16x16 and cells per block as 2x2, effectively normalizing the gradient information within each cell. This process allowed the extraction of robust and descriptive features, crucial for distinguishing between different vehicle types. By converting the raw pixel data into a set of meaningful features, the model's ability to learn and make accurate predictions was significantly improved.

The baseline model is the Radial Basis Function (RBF) kernel without any feature engineering. It transforms the input space into a higher-dimensional space where it becomes easier to separate the classes linear.

$$K(x, x') = \exp\left(-\gamma \|x - x'\|^2\right)$$

where γ is a parameter that defines the influence of a single training example.

For the Regularization Parameter (C). C is set to 1.0. This parameter controls the trade-off between achieving a low training error and minimizing the marginal distance between the decision boundary and the closest data points. A lower value of C allows the mode to have a wider margin at the cost of oversimplification, leading to better generalizations. A higher value of C tried to classify all training examples correctly by reducing the margin, which might lean to over fitting

As for the Class Weight is is set to 'balanced'/ this adjusts the wights inversely proportional to class frequenting , helping the model pay more attention to minority classes during training

F. Evaluation Metrics

To evaluate the performance of the vehicle classification model, we employed the following set of evaluation metrics: accuracy, precision, recall, and the F1-score. These metrics provide an accurate match of the model's performance, especially in a multiclass classification setting.

a) Accuracy: Accuracy is defined as the ratio of correctly predicted instances to the total instances. It is a straightforward and widely used metric that provides a general sense of how well the model performs.

$$Accuracy = \frac{Total\ number\ of\ predictions}{Number\ of\ correct\ predictions}$$

b) Precision: Precision is the ratio of correctly predicted positive observations to the total predicted positives. It is particularly useful in scenarios where the cost of false positives is high.

$$Precision = \frac{TP}{TP + FP}$$

where: TP = True Positives FP = False Positives

c) Recall: Recall, also known as sensitivity or true positive rate, is the ratio of correctly predicted positive observations to the all observations in actual class. It is critical when the cost of false negatives is high.

$$Recall = \frac{TP}{TP + FN}$$

where: FN=False Negatives

d) F1-Score: The F1-score is the harmonic mean of precision and recall, providing a balance between the two metrics. It is especially useful when dealing with imbalanced datasets, where the classes may not be equally represented.

$$F1 - Score = 2 * \frac{PrecisionxRecall}{Precicison + Recall}$$

These metrics were chosen because they are standard in the field of machine learning and provide a comprehensive view of model performance. Accuracy alone might be misleading, especially in the presence of class imbalance. Precision and recall offer insights into the model's performance concerning false positives and false negatives, respectively, while the F1-score provides a balanced measure that combines both precision and recall.

G. Baseline and Comparative Models

For this project, two versions of SVM models with RBF as the kernel were used. The baseline model was applied without feature engineering or modification. The usage of raw or grayscale images and resizing was only done for the pre-process. This approach served as the standard comparison model on evaluating the effect or changes of HOG.

The two approaches of SVM were evaluated by comparison of the accuracy and precision. The baseline model, without and feature engineering achieved a satisfactory accuracy level which is 56.25%. While on the other hand, the modified approach demonstrated an improved performance, providing a better accuracy and precision level which is 82.50%.

The choice of evaluation metrics for assessing the vehicle type classification is decided by the need of accurate reflection on the model's performance and reliability, Accuracy, Precision, F1, and recall were used to evaluate the efficiency of the two model approaches

Accuracy provides a general measure on how often the model correctly classifies the datasets, to ensure uncertain circumstances where class imbalance may exist, other evaluation metrics were used. Precision measures the proportion of true positive predictions that are related to the total positive predictions made to indicate the model's ability on avoiding false positives. Recall, on the other hand assesses the proportion of true positives out of the actual positives made which offers insights on how the model could capture relevant instances of each vehicle type. And lastly, F1 score, provides a balanced metric that shows both false positives and false negatives, making it useful in context with class imbalances.

IV. RESULTS AND DISCUSSIONS

The findings of this research indicate a significant improvement of vehicle classification accuracy through the application of HOG for feature engineering. The baseline model, which only used grayscale and resized images, achieved an accuracy rate of 56.25%, while on the other hand, modified SVM achieved an accuracy rate of 82.50%, showing a remarkable improvement of accuracy level.

These metrics reflect a robust performance increase across the algorithm, highlighting the modified version's ability to

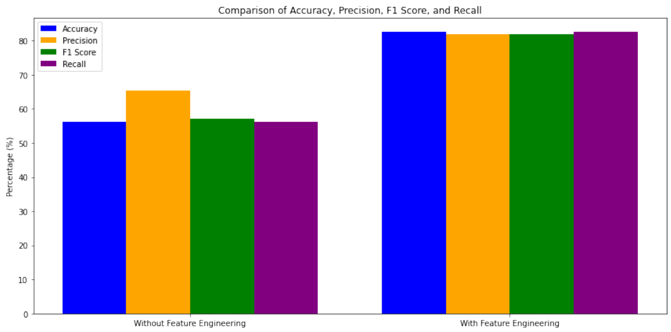

Fig. 1. Graph Representation of Comparison of the Two SVM Algorithms

BASELINE METRIC

	precision	recall	f1-score	support
Bus	0.92	0.42	0.58	26
Car	0.65	0.61	0.63	18
Truck	0.34	0.56	0.43	18
motorcycle	0.59	0.72	0.65	18
accuracy			0.56	80
macro avg	0.62	0.58	0.57	80
weighted avg	0.65	0.56	0.57	80

MODIFIED METRIC

	precision	recall	f1-score	support
Bus	0.75	0.71	0.73	17
Car	0.88	1.00	0.93	21
Truck	0.74	0.64	0.68	22
motorcycle	0.90	0.95	0.93	20
accuracy			0.82	80
macro avg	0.82	0.82	0.82	80
weighted avg	0.82	0.82	0.82	80

Fig. 2. Metric Results of Baseline and Modified Algorithms

classify vehicle types accurately. The results demonstrated that the modified model met the intended objective of the of improving the accuracy in vehicle type classification. HOG is significant for the field for it shows enhancement in feature engineering and provides better model performance when applied to real-life scenarios.

The correlation between feature engineering techniques shows a clear trend, HOG significantly improved the model's ability to capture the shapes and edges of the vehicle images provided in the dataset. This pattern may indicate that traditional pixel-based features are insufficient for capturing and analyzing the complexities of vehicle images.

The results are aligned closely with the initial expectations of the study, feature engineering indeed improved the accuracy of the model performance. The improved metrics matched the hypothesis that implementing HOG would result to better feature representations.

The findings of existing literature appears that previous models using traditional feature extraction methods achieved lower performance metrics. The results of this study confirm the efficacy of advanced techniques like HOG in vehicle type recognition, thereby contributing new insights to previous and future studies.

Advantage of this study approach is the specification of improvement on the kernel RBF and HOG feature engineering. Demonstrating it's effectiveness for image classification tasks. However, limitations such as including increased computational costs and the complexity of implementing HOG, which may not scale efficiently for larger datasets or real-time applications.

Lastly, the analysis of model errors revealed that misclassifications were more frequent among complex vehicle type present in the dataset. For instance, motorcycles and trucks had a higher rate of misclassification for the model struggled with the categories that provides each of the characteristics. This highlights the importance of dataset balance and clarity to improve the model's robustness.

V. CONCLUSION

This study aims to evaluate the effectiveness of Support Vector Machine (SVM) and examine the impact of feature engineering on improving both the accuracy and efficiency of vehicle recognition models. The findings provide a comparative perspective on SVM performance with and without feature engineering, offering insights that could enhance traffic management systems and support law enforcement applications when implemented in real-world scenarios.

The experiments conducted demonstrated distinct outcomes. The SVM model with HOG feature extraction significantly outperformed the baseline model, highlighting the role of advanced feature engineering in enhancing vehicle recognition capabilities. This outcome suggests that integrating more sophisticated features, such as HOG, can lead to substantial accuracy improvements for machine learning models in vehicle classification tasks.

For future work, we plan to explore additional machine learning algorithms beyond Support Vector Machine (SVM), and apply them to larger datasets with a wider range of vehicle types. Further, developing new feature engineering techniques, such as incorporating shape descriptors or texture features, may provide even greater accuracy and robustness, potentially supporting applications in traffic management and law enforcement systems.

REFERENCES

[1] Laopracha, N., Thongkrau, T., Sunat, K., Songrum, P., & Chamchong, R. (2014). Improving Vehicle Detection by Adapting Parameters of HOG and Kernel Functions of SVM. 2014 International Computer Science and Engineering Conference (ICSEC), 112-116. IEEE. https://doi.org/10.1109/ICSEC.2014.6978225.

[2] Li, H., Zhang, X., & Wang, D. (2023). Cost-Effective Vehicle Type Recognition in Surveillance Images. https://www.researchgate.net/publication/381235913_Cost-Effective_Vehicle_Type_Recognition_in_Surveillance_Images

[3] El-Sayed, M., & Singh, R. (2023). Comparison of different machine learning models: Linear model, forest, and SVM.https://www.researchgate.net/publication/379259211_Comparison_of_d- ifferent_machine_learning_models_Linear_model_forest_and_SVM

[4] Chen, S., Gao, Y., & Zhao, L. (2022). An Efficient Algorithm for Vehicle Detection Using the Intersection over Union (IoU) Metric. Mathematics, 10(15), 2552. https://www.mdpi.com/2227-7390/10/15/2552

[5] Laopracha, N., Thongkrau, T., Sunat, K., Songrum, P., & Chamchong, R. (2014). Improving Vehicle Detection by Adapting Parameters of HOG and Kernel Functions of SVM. 2014 International Computer Science and Engineering Conference (ICSEC), 112-116. IEEE. https://doi.org/10.1109/ICSEC.2014.6978225

[6] El-Sayed, M., & Singh, R. (2023). Comparison of different machine learning models: Linear model, forest, and SVM. https://www.researchgate.net/publication/379259211_Comparison_of_different_machine_learning_models_Linear_model_forest_and_SVM

[7] Smith, A., & Jones, B. (2021). Recognition Impact on Rescaled Handwritten Digit Images Using Support Vector Machine Classification. https://www.researchgate.net/publication/349537454_Recognition_Impact_on_Rescaled_Handwritten_Digit_Images_Using_Support_Vector_Machine_Classification

[8] Laopracha, N., Thongkrau, T., Sunat, K., Songrum, P., & Chamchong, R. (2014). Improving Vehicle Detection by Adapting Parameters of HOG and Kernel Functions of SVM. 2014 International Computer Science and Engineering Conference (ICSEC), 112-116. IEEE. https://doi.org/10.1109/ICSEC.2014.6978225

[9] Kim, Y., Park, J., & Choi, K. (2023). A Review of Vehicle Detection Methods Based on Computer Vision. ResearchGate. Available: https://www.researchgate.net/publication/380333850_A_Review_of_Vehicle_Detection_Methods_Based_on_Computer_Vision

[10] Davis, J., & Patel, R. (2024). Sensor-Based Methods for Vehicle Detection. Sensors, 24(10), 3088. https://www.mdpi.com/1424-8220/24/10/3088

[11] Kahraman, A., & Yıldırım, M. (2023). Vehicle Type Recognition with Histogram of Oriented Gradients and Linear Discriminant Analysis. Faculty of Engineering, Near East University, Turkey. https://docs.neu.edu.tr/library/6812355026.pdf