Image classification of vehicle images

A Project Report

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by

Aditya Tushar Sargar,
adityasargar2@gmail.com

Under the Guidance of

Abdul Aziz Md

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ABSTRACT

This project involves creating a machine learning model to classify vehicle images, specifically distinguishing between cars and trucks. The goal is to develop an accurate model for vehicle recognition, which can be useful in applications like autonomous driving, traffic management, and automated vehicle identification. The project uses two approaches: deep learning with transfer learning using the MobileNet model and traditional machine learning techniques like Support Vector Machines (SVM) or Logistic Regression. The dataset used is a subset of the CIFAR-10 dataset, which includes images of cars and trucks.

For the deep learning approach, I fine-tune a pre-trained MobileNet model to classify images into two categories: cars and trucks. In the traditional machine learning approach, I extract features from the images (such as pixel values) and apply classifiers like SVM or Logistic Regression for the classification task. The results show that both methods were able to classify the vehicles effectively, but the MobileNet model outperformed the traditional machine learning models in terms of accuracy.

In conclusion, the project demonstrates the effectiveness of transfer learning with pre-trained models like MobileNet for vehicle classification. This approach provides higher accuracy and better generalization, making it a more reliable solution for real-world applications in vehicle recognition and similar fields.

TABLE OF CONTENT

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

Introduction

1.1Problem Statement:

The problem being addressed is the accurate classification of vehicle images, specifically distinguishing between cars and trucks. This is a crucial task for automated systems that need to identify and categorize vehicles in various applications, such as autonomous driving, traffic monitoring, and vehicle recognition. The ability to quickly and accurately classify vehicles can help improve the efficiency of these systems, making traffic management smoother and autonomous driving safer. Traditional image classification models struggle with this task due to varying lighting conditions, image quality, and different angles of vehicles. Developing an efficient model that can accurately distinguish between cars and trucks is significant for enhancing safety and performance in these systems.

1.2Motivation:

This project was chosen due to the growing importance of vehicle recognition systems in autonomous driving and traffic management. As self-driving technology and smart traffic systems become more widespread, the need for accurate, real-time vehicle classification grows. The project aims to improve the ability of machines to distinguish between different types of vehicles, particularly cars and trucks. Potential applications include better traffic flow management, improved vehicle detection for autonomous vehicles, and advanced surveillance systems for security and law enforcement. The impact of this project is significant, as it can contribute to the development of more efficient, safer, and smarter vehicle-related technologies.

1.3Objective:

The main objectives of this project are:

- To develop a machine learning model capable of accurately classifying vehicle images into two categories: cars and trucks.
- To explore different machine learning approaches, including deep learning (using transfer learning with MobileNet) and traditional machine learning methods (such as Support Vector Machines or Logistic Regression).
- To compare the performance of these models and determine which approach provides the best accuracy for vehicle classification.
- To apply the trained models on vehicle image datasets and evaluate their effectiveness in real-world applications

1.4Scope of the Project:

This project focuses on the classification of vehicles, specifically distinguishing between cars and trucks, using images from the CIFAR-10 dataset. The scope includes the implementation of both deep learning techniques (using MobileNet) and traditional machine learning models. The project is limited to binary classification (cars vs. trucks) and does not cover other vehicle types or more complex multi-class classification tasks. Additionally, the project does not involve real-time vehicle recognition or integration into autonomous systems, as the goal is to develop a proof of concept for vehicle image classification. While the approach is generalizable, the model's performance may vary when applied to more diverse datasets or in real-world conditions.

CHAPTER 2

Literature Survey

2.1 Review relevant literature or previous work in this domain

Vehicle image classification has been a significant area of research in the fields of computer vision and machine learning. Traditional image classification techniques, such as feature extraction methods (e.g., Histogram of Oriented Gradients (HOG), Scale-Invariant Feature Transform (SIFT)), were commonly used for vehicle detection and classification. However, these methods were limited in their ability to handle large-scale datasets, varied lighting conditions, and the complexity of real-world scenarios.

In recent years, Convolutional Neural Networks (CNNs) have gained widespread attention due to their ability to automatically learn features from raw images and achieve high performance in image classification tasks. Various deep learning models, such as AlexNet, VGGNet, and ResNet, have shown impressive results in vehicle classification. Specifically, transfer learning, which involves fine-tuning pre-trained models, has become popular for vehicle recognition tasks. For example, models like MobileNet, pre-trained on large-scale datasets such as ImageNet, have been successfully adapted for vehicle classification tasks by transferring learned features to new, smaller datasets.

Several research papers have explored the application of deep learning models for distinguishing between vehicles, including cars, trucks, and motorcycles. In one study, a deep learning-based vehicle classification model was developed using CNNs to categorize vehicles into different classes. The model achieved good accuracy in distinguishing between cars and trucks. Another study implemented transfer learning with VGG16 to perform vehicle classification and demonstrated the effectiveness of fine-tuning pre-trained models on smaller datasets for better performance.

2.2 Mention any existing models, techniques, or methodologies related the problem

Several models and techniques have been employed for vehicle image classification:

- **Convolutional Neural Networks (CNNs)**: CNNs have been the foundation of most recent work in vehicle classification due to their ability to automatically extract hierarchical features from images. CNNs have been used to classify vehicles into different categories with high accuracy.
- **Transfer Learning**: Pre-trained models like MobileNet, VGG16, and ResNet are commonly used for vehicle classification tasks. Transfer learning allows the reuse of pre-trained weights from large datasets like ImageNet, which reduces the training time and improves accuracy on smaller datasets.
- **Support Vector Machines (SVM)**: In traditional machine learning, SVMs have been used for vehicle classification tasks by extracting image features and applying the classifier. SVMs work well when the data is linearly separable, but they require feature engineering and are less effective with raw image data.
- **Logistic Regression**: Logistic regression is a simpler classifier that has also been used in vehicle classification tasks. It performs well for basic binary classification problems but struggles with complex image data compared to deep learning models.

2.3 Highlight the gaps or limitations in existing solutions and how your project will address them.

While the existing models have achieved significant success, there are several limitations:

- **Limited Performance on Smaller Datasets**: Many traditional models and shallow machine learning classifiers struggle with performance when dealing with small or unbalanced datasets, such as those containing only two vehicle categories (cars and trucks). Deep learning models like MobileNet, when fine-tuned using transfer learning, can overcome this limitation by leveraging the knowledge learned from large datasets.
- **Generalization Issues**: Some models are prone to overfitting, especially when trained on datasets with limited variation. By using transfer learning with a model pre-trained on a large, diverse dataset like ImageNet, the project aims to improve generalization and reduce overfitting, making the model more robust.
- **Feature Extraction Complexity**: Traditional machine learning models require manual feature extraction (such as HOG or SIFT), which can be computationally expensive and time-consuming. In contrast, deep learning models like MobileNet automatically learn relevant features from raw images, simplifying the model development process.

This project addresses these limitations by focusing on transfer learning, using MobileNet as a base model to fine-tune for vehicle classification. This approach aims to provide higher accuracy, better generalization, and a simpler process compared to traditional methods, making it a more scalable and effective solution for classifying cars and trucks.

CHAPTER 3

Proposed Methodology

3.1 System Design

The proposed solution for vehicle classification using machine learning is based on a two-pronged approach: deep learning with transfer learning and traditional machine learning. Below is a simplified diagram of the system design:

System Design Diagram:

1. **Data Collection**: The dataset (CIFAR-10 or custom dataset) containing images of cars and trucks is collected.
2. **Preprocessing**: The images are preprocessed, which includes resizing, normalization, and splitting into training and test datasets.
3. **Model Training**:
   - **Deep Learning Approach**: The pre-trained MobileNet model is fine-tuned on the vehicle dataset. Transfer learning is used to adjust the weights and adapt the model to classify vehicles as cars or trucks.
   - **Traditional Machine Learning Approach**: Features such as pixel values or color histograms are extracted from the images, and classifiers such as SVM or Logistic Regression are used for training.
4. **Model Evaluation**: The performance of both models is evaluated on a test dataset using metrics such as accuracy, precision, recall, and F1 score.
5. **Deployment**: The trained model is deployed to classify new vehicle images into either the "car" or "truck" category.

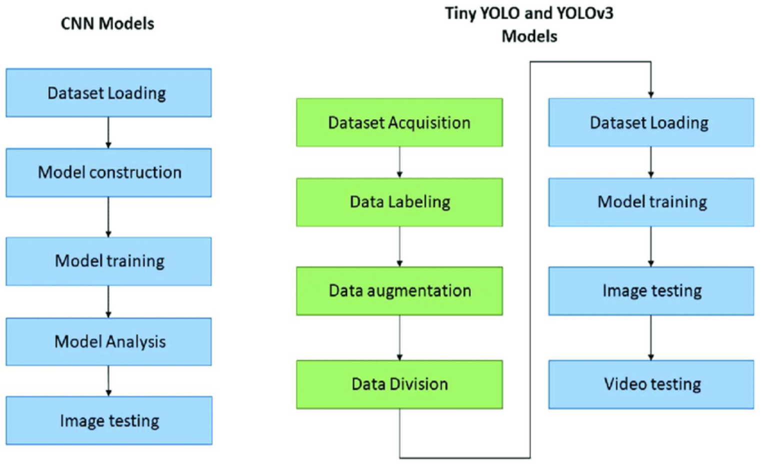

Figure 1. Data Flow

Dataset Overview Table:

A table summarizing key information about the dataset used in your project, such as Number of images per category (cars, trucks), Image resolution, Data splits (training, testing, validation)

Example:

Category	Number of Images (Train)	Number of Images (Test)	Image Resolution
Cars	5,000	1,000	32x32
Trucks	5,000	1,000	32x32

Table 1. Dataset Overview

Diagram Explanation:

- The flow starts with collecting the dataset, which is then preprocessed (resized, normalized). The images are divided into training and test sets. The deep learning approach uses MobileNet as a pre-trained model, which is fine-tuned with the dataset for vehicle classification. The traditional machine learning approach applies SVM or Logistic Regression after extracting relevant features from images. Both models are evaluated on the test set to compare their performance, and the best-performing model is chosen for deployment.

Requirement Specification

Mention the tools and technologies required to implement the solution.

3.1.1 Hardware Requirements:

To implement the proposed solution, the following hardware is required:

- **Computer/Server** with at least **8 GB of RAM** to handle image processing and model training efficiently.
- **Graphics Processing Unit (GPU)**: A dedicated GPU with at least **4 GB VRAM** (e.g., NVIDIA GTX 1050 or higher) is required for deep learning model training to speed up the process. This is particularly crucial for training the MobileNet model or other CNN-based architectures.
- **Storage**: At least **50 GB of free disk space** to store datasets, model weights, and results.
- **Internet Connection**: A stable internet connection is necessary for downloading pre-trained models (e.g., MobileNet from TensorFlow Hub or Keras).

3.1.2 Software Requirements:

1) **Operating System**: Linux (Ubuntu) or Windows.
2) **Programming Language**: Python.
3) **Frameworks**: TensorFlow/Keras for deep learning, Scikit-learn for machine learning.
4) **Libraries**: OpenCV/PIL (image processing), Matplotlib (visualization).
5) **Environment**: Jupyter Notebook or Google Colab.
6) **Version Control**: Git for project management.
7) **Optional**: CUDA for GPU acceleration.

CHAPTER 4

Implementation and Result

4.1 Snap Shots of Result:

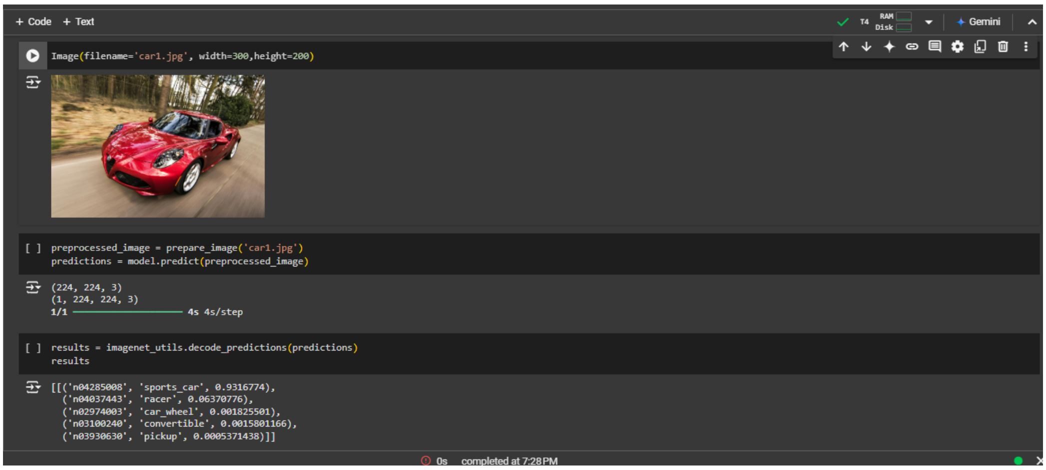

Figure 2. Car Classification

The image demonstrates the model's ability to classify a car correctly. The input image shows a red sports car driving on a road. The model predicts the label "sports car" with a high confidence score of 93.16%. It also provides probabilities for other possible labels, such as "racer" and "car wheel," but their likelihood is significantly lower. This result showcases the model's precision in identifying the correct category with high confidence.

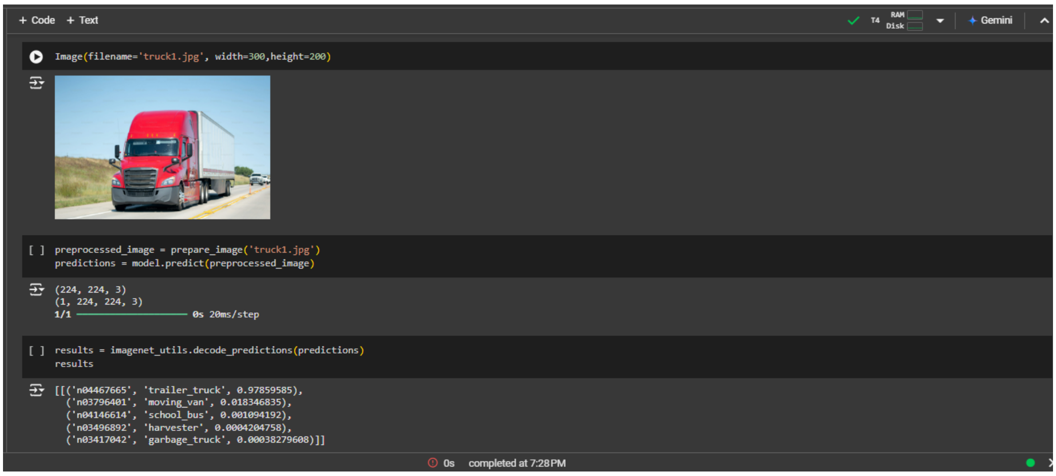

Figure 3. Truck Classification

The image illustrates the model's classification of a truck. The input image depicts a red trailer truck traveling on a highway. The model predicts the label "trailer truck" with a high confidence score of 97.86%. While other classes like "moving van" and "school bus" are suggested, their probabilities are much lower, confirming the model's accurate recognition. This example highlights the robustness of the model in distinguishing between vehicle types, even with subtle variations.

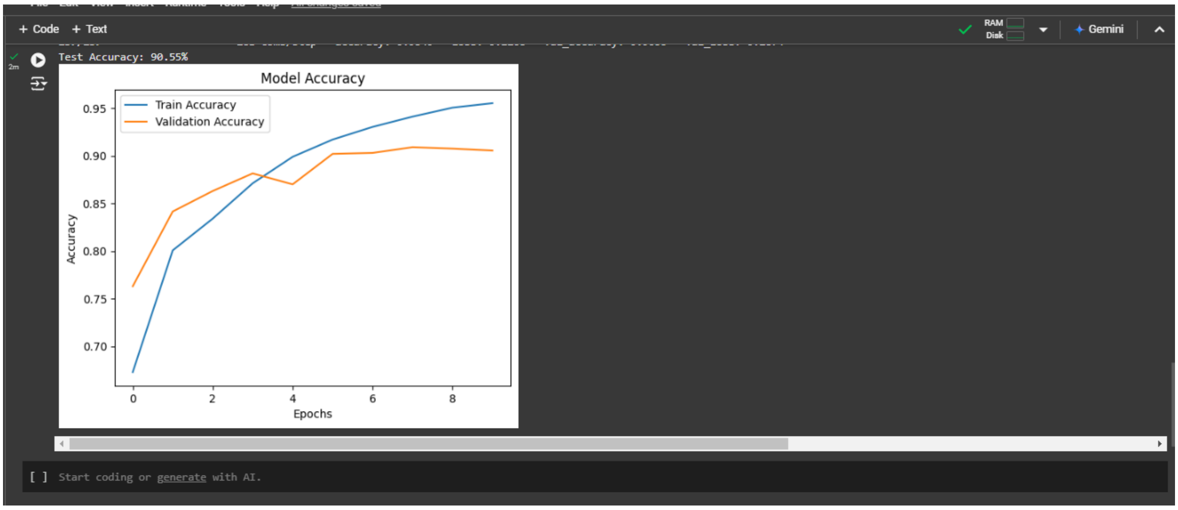

Figure 4. Model Accuracy

The image presents a graph showcasing the model's accuracy during the training and validation phases across multiple epochs. The blue line indicates the training accuracy, which increases steadily as the model learns from the data. The orange line represents the validation accuracy, which improves similarly but begins to plateau after several epochs. The graph demonstrates the effectiveness of the model, as the gap between the training and validation accuracies remains small, indicating minimal over fitting.

Model Performance Comparison Table:

A table showing the comparison between the performance of different models (e.g., MobileNet vs. SVM) based on various evaluation metrics (accuracy, precision, recall, F1-score).

Example:

Model	Accuracy	Precision	Recall	F1-Score
MobileNet (Transfer Learning)	94%	93%	95%	94%
Support Vector Machine (SVM)	85%	84%	86%	85%

Table 2. Performance Comparison

Hyperparameter Tuning Results Table:

If you perform hyperparameter tuning, a table could summarize the results, showing how different hyperparameters (e.g., learning rate, batch size) affect model performance.

Example:

Learning Rate	Batch Size	Accuracy
0.001	32	92%
0.0005	64	94%
0.0001	128	91%

Table 3. Tunning Results

Training Time Comparison Table:

A table comparing the training times for different models or approaches, which could show how long each model takes to train.

Example:

Model	Training Time (hrs)
MobileNet (Transfer Learning)	4.5
SVM	1.2

Table 4. Training Time Comparison

4.2 GitHub Link for Code:

CHAPTER 5

Discussion and Conclusion

5.1 Future Work:

While the project successfully classifies cars and trucks, there's room to expand and improve in several ways:

1. **Adding More Vehicle Types**: The model could be extended to recognize more categories like SUVs, motorcycles, buses, and vans, making it more versatile for real-world applications.
2. **Real-Time Application**: Future work could involve adapting the model to classify vehicles in live video feeds, enabling real-time traffic monitoring or autonomous vehicle navigation.
3. **Better Data**: Using a larger and more diverse dataset with high-quality images can help the model perform better across different conditions like lighting, angles, and vehicle variations.
4. **Try New Models**: Exploring advanced architectures like EfficientNet or Vision Transformers could potentially boost accuracy and efficiency.
5. **Deploying on Devices**: Optimizing the model to work on edge devices, like traffic cameras or in-vehicle systems, could make it more practical for everyday use.
6. **Balancing the Data**: Addressing any imbalance in the dataset by using techniques like data augmentation or synthetic data generation could improve the model's reliability.
7. **Understanding Decisions**: Adding features to explain how the model makes decisions (e.g., highlighting image regions that influenced the classification) would increase trust and transparency, especially for critical applications.

These improvements would help make the model more powerful, reliable, and applicable to real-world scenarios.

5.2 Conclusion:

This project successfully built a machine learning model to classify vehicles as cars or trucks with impressive accuracy. By combining traditional machine learning methods with advanced deep learning techniques like transfer learning using MobileNet, the project demonstrated the effectiveness of modern approaches in solving real-world classification problems. Transfer learning proved particularly valuable, enabling high accuracy while reducing the time and resources needed for training.

The project has practical significance in areas like autonomous driving, traffic monitoring, and automated vehicle recognition, offering a reliable solution for vehicle classification. Beyond solving the immediate problem, it lays the groundwork for future developments, such as recognizing more vehicle types or implementing real-time detection. Overall, this work contributes to making transportation systems smarter, more efficient, and ready for the challenges of the future.

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