EE4016 Group Project Report
Vehicle Type Recognition System

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Abstract

Vehicle classification plays a critical role in various applications, including traffic management, surveillance, and autonomous driving. This report presents a comprehensive study on the development and evaluation of a vehicle classification system, comparing traditional machine learning techniques such as Support Vector Machines (SVMs) with modern deep learning-based approaches like Convolutional Neural Networks (CNNs) and transfer learning.

The primary objective of the research is to design models capable of accurately classifying vehicles into four distinct categories: bus, car, motorcycle, and truck. The study evaluates the performance of a linear SVM model, which relies on manually extracted features using the Histogram of Oriented Gradients (HOG) method, against a CNN-based model leveraging the ResNet50V2 architecture. The CNN model is pre-trained on the large ImageNet dataset and fine-tuned using a dataset of vehicle images. Data augmentation techniques, such as rotation, shifting, flipping, and zooming, are applied to enhance the diversity of the training data and improve the model's generalization to unseen data.

The SVM model serves as a baseline, providing insights into the effectiveness of traditional machine learning approaches. It is trained using HOG features, which capture essential shape and edge information, and evaluated using metrics such as accuracy, precision, recall, and F1-score. While SVM demonstrates reasonable performance, particularly for simpler categories like motorcycles, it struggles with overlapping and visually similar classes such as trucks and buses due to its linear decision boundaries and reliance on predefined features.

In contrast, the ResNet50V2-based CNN model employs a two-phase training process. The first phase involves freezing the pre-trained layers to leverage features learned from ImageNet, while the second phase fine-tunes the higher layers to adapt the network to the vehicle classification task. This deep learning approach significantly outperforms the SVM model, achieving higher accuracy and better generalization, as evidenced by a confusion matrix and detailed classification metrics. Specifically, the CNN model demonstrates its ability to handle the variability in vehicle appearances and reduce misclassifications through its hierarchical feature extraction capabilities.

The results of this study highlight the limitations of the SVM model, which, though effective for smaller and less complex datasets, is outperformed by CNNs in scenarios requiring the modelling of non-linear relationships and diverse feature spaces. The CNN model's superior performance validates the hypothesis that transfer learning, combined with data augmentation, can significantly enhance classification accuracy, even with a limited dataset. However, challenges remain, particularly in the misclassification of visually similar vehicle types, such as motorcycles and cars, underscoring the need for further research.

This report contributes to the growing body of research on vehicle classification by providing a comparative analysis of SVM and CNN approaches. It demonstrates the transformative potential of deep learning techniques in improving classification systems, making them more efficient, scalable, and accurate. The findings have practical implications for real-world applications, including traffic surveillance, autonomous driving, and vehicle recognition systems. Finally, this research offers recommendations for future work, such as exploring kernelized SVMs, expanding datasets, and adopting more advanced CNN architectures, to further enhance the accuracy and robustness of vehicle classification models.

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Chapter 1: Introduction

The classification of vehicles has become an essential component of modern transportation systems, addressing various societal needs such as traffic management, urban planning, law enforcement, and the advancement of autonomous vehicles. Accurate identification and classification of vehicles from images are foundational to intelligent transportation systems (ITS), enabling better decision-making in real-time traffic scenarios and fostering the development of advanced driver assistance systems (ADAS). The challenge lies in designing a robust system capable of recognizing vehicles under diverse conditions, such as variations in lighting, orientation, and environmental factors. This study leverages advancements in deep learning, particularly Convolutional Neural Networks (CNNs), to develop a vehicle classification model that achieves high accuracy and scalability.

The traditional approaches to vehicle classification, which relied on manually engineered features, were often constrained by their inability to generalize across complex datasets. These methods required domain-specific expertise to extract features like edges, textures, and shapes and suffered from limited adaptability to real-world variations. The advent of deep learning, particularly CNNs, has transformed the field by enabling end-to-end learning, where hierarchical features are automatically extracted from raw image data. This project capitalizes on the capabilities of CNNs, employing the ResNet50V2 architecture, a pre-trained model renowned for its success in computer vision tasks, and fine-tuning it for the specific requirements of vehicle classification.

1.1 BACKGROUND

The rise in urbanization and the proliferation of vehicles have placed significant pressure on existing transportation systems, necessitating innovative solutions to manage and monitor traffic effectively. Automated vehicle classification is one such solution, contributing to applications such as toll collection, traffic surveillance, congestion monitoring, and automated parking systems. Furthermore, vehicle classification is crucial in autonomous vehicles, where accurate identification of surrounding vehicles ensures safe navigation and decision-making.

Historically, vehicle classification relied on traditional computer vision techniques such as edge detection, contour matching, and handcrafted feature extraction. While these methods achieved modest success in controlled environments, their performance degraded significantly in real-world scenarios characterized by occlusions, dynamic backgrounds, and varying environmental conditions. With the emergence of deep learning, particularly CNNs, the limitations of traditional approaches have been addressed. CNNs have demonstrated exceptional performance in image recognition tasks by learning hierarchical features directly from the data, eliminating the need for manual feature engineering. This research builds upon this progress, leveraging CNNs to design a vehicle classification system capable of robust and accurate performance.

1.2 CONTEXT

In the context of intelligent transportation systems, vehicle classification is a foundational task that supports a wide array of applications. For example, traffic management systems rely on real-time vehicle classification to monitor congestion levels and optimize traffic flow. Similarly, toll collection systems use vehicle classification to apply differential pricing based on vehicle types, such as distinguishing between commercial trucks and private cars. Additionally, law enforcement agencies employ vehicle classification systems for surveillance and monitoring purposes, identifying vehicles that violate traffic regulations.

Despite its critical importance, vehicle classification remains a challenging problem due to the variability in vehicle appearances and the environmental conditions in which images are captured. Differences in vehicle size, color, shape, and orientation, coupled with varying lighting conditions and background clutter, make the task inherently complex. Traditional classification methods often fail to handle these variations effectively. By contrast, deep learning models, particularly those based on CNNs, have proven adept at learning robust and invariant features from large datasets, enabling accurate classification even in challenging scenarios.

This research not only focuses on the use of ResNet50V2, a pre-trained CNN model, for vehicle classification but also delves into the reasons why traditional methods of vehicle classification are being replaced. Specifically, it examines the limitations of traditional approaches, such as those that rely on Support Vector Machines (SVM) and highlights how modern deep learning techniques provide superior performance. To address the specific requirements of this task, the CNN model is fine-tuned using transfer learning, enabling it to achieve high accuracy even with a relatively small dataset. Furthermore, advanced data augmentation techniques are applied to enhance the diversity of the training data, thereby improving the model's generalization capability and effectiveness in real-world scenarios.

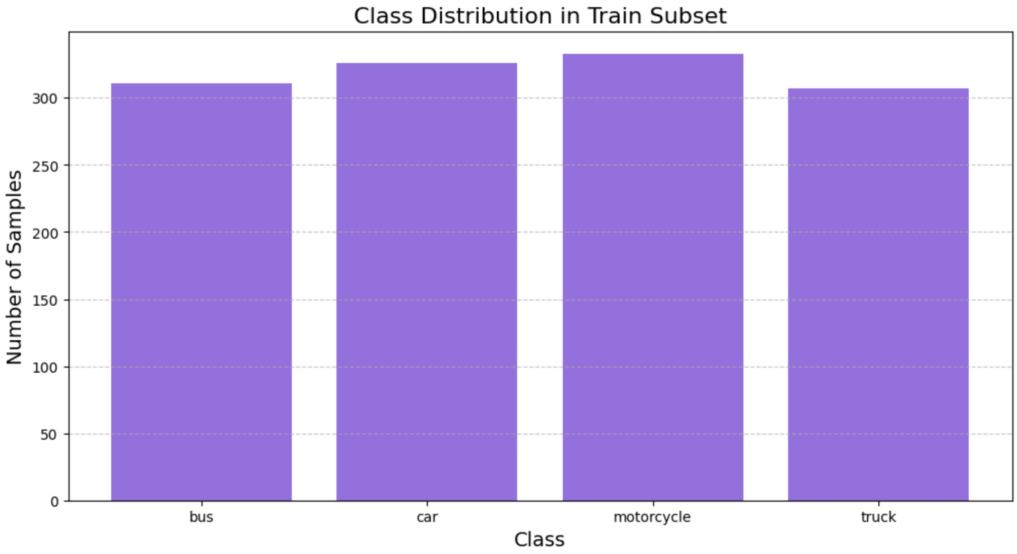


Figure of class distribution in train subset

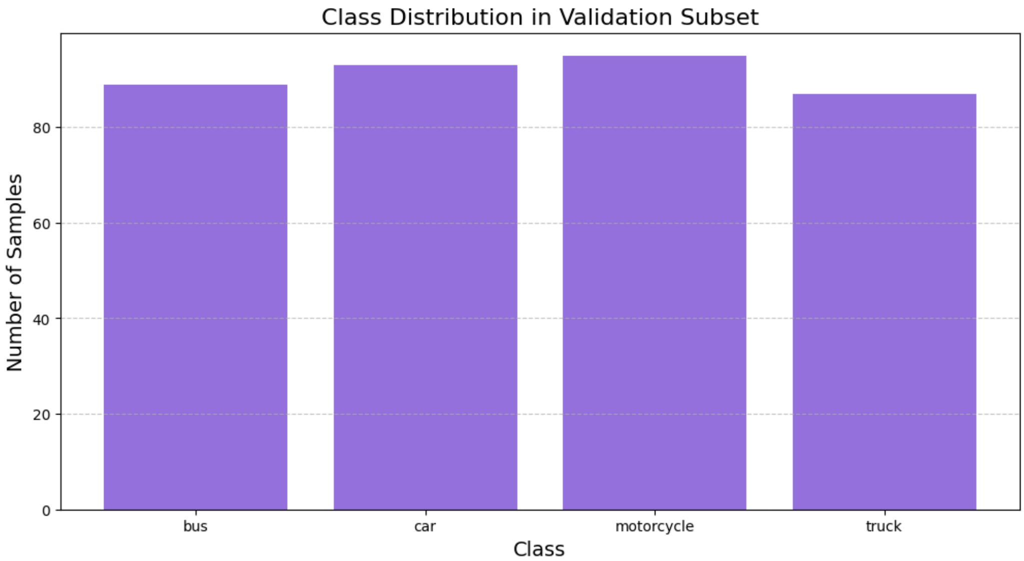


Figure of class distribution in validation subset

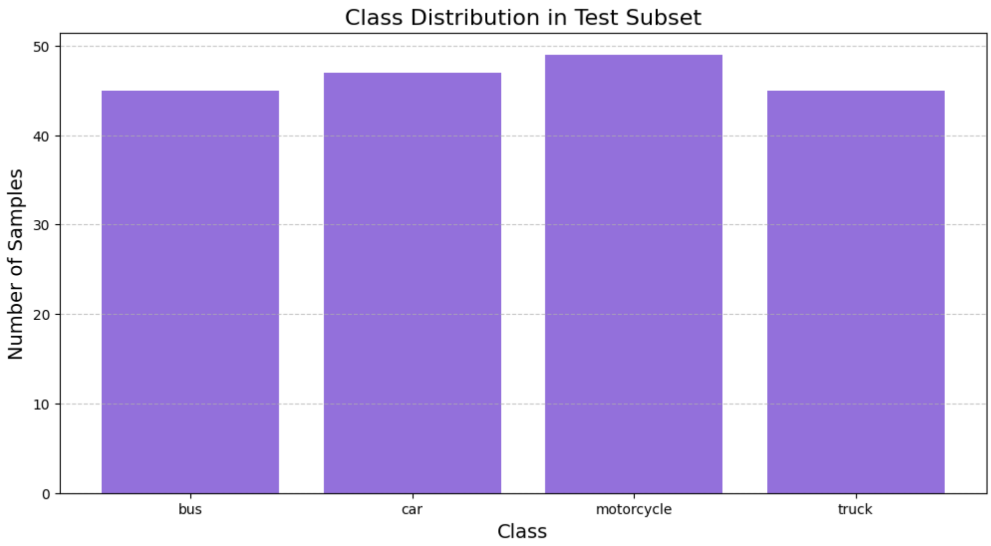


Figure of class distribution in test subset

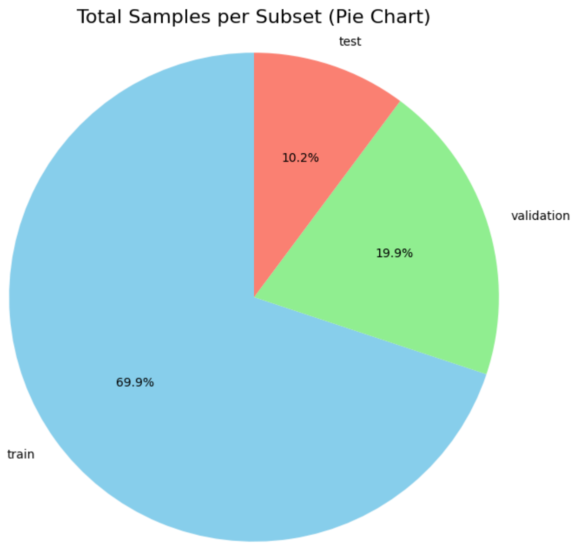


Figure of total samples per subset

1.3 PURPOSES

The primary purpose of this research is to develop an automated vehicle classification model using deep learning techniques, with the aim of categorizing vehicles into four distinct classes: bus, car, motorcycle, and truck. Also, the developed CNN method will compare to the traditional method, namely SVM. The specific goals of this study include:

1. Implementing a CNN-based model, using the ResNet50V2 architecture, to achieve high classification accuracy.

2. Utilizing transfer learning to adapt the pre-trained ResNet50V2 model to the domain-specific task of vehicle classification, leveraging its pre-existing knowledge of generic visual features.
3. Enhancing the model's generalization capability through data augmentation, which artificially increases the diversity of the training dataset by applying transformations such as rotation, flipping, and scaling.
4. Evaluating the model's performance using standard metrics, including accuracy, precision, recall, and F1-score, to provide a comprehensive assessment of its classification ability.
5. Comparing the traditional technique vehicle classification (SVM) to CNN

Through these objectives, this research seeks to address the challenges associated with vehicle classification and contribute to the development of reliable and scalable deep learning solutions for real-world applications.

1.4 SIGNIFICANCE, SCOPE, AND DEFINITIONS

This research is significant in its potential to address critical challenges in vehicle classification, offering a solution that is both accurate and scalable. The ability to classify vehicles accurately has wide-ranging implications, from improving traffic management and enhancing road safety to supporting the development of autonomous vehicles. By leveraging deep learning techniques, this study advances the state of the art in vehicle classification, providing a robust framework that can be extended to other image recognition tasks in intelligent transportation systems.

The scope of this research is limited to the classification of vehicles into four categories: bus, car, motorcycle, and truck. While these categories represent a broad range of vehicles encountered in urban environments, the study does not delve into finer-grained classification, such as distinguishing between different makes and models of cars. The dataset used in this research comprises images captured under diverse conditions, ensuring that the model is trained on a representative sample of real-world data.

To ensure clarity, several key terms used throughout this report are defined below:

- **Convolutional Neural Networks (CNNs):** A class of deep learning algorithms specifically designed for image processing tasks, characterized by their ability to learn spatial hierarchies of features from input data.
- **Transfer Learning:** A technique in deep learning where a model pre-trained on a large dataset is fine-tuned for a specific task, leveraging its existing knowledge to improve performance on domain-specific data.
- **Data Augmentation:** A process used to artificially increase the size and diversity of a training dataset by applying transformations such as rotation, flipping, scaling, and color adjustments to input images.

- **Support Vector Machine (SVM):** a supervised machine learning algorithm commonly used for classification and regression tasks. The primary goal of SVM is to find the optimal hyperplane that separates data points from different classes with the maximum margin, ensuring better generalization to unseen data.
- **Histogram of Oriented Gradients (HOG):** a feature extraction technique commonly used in computer vision tasks, particularly for object detection and recognition. HOG works by capturing the shape and structure of objects in an image through the distribution of intensity gradients and edge directions.

1.5 THESIS OUTLINE

This report is structured into six chapters, each addressing a critical aspect of the research:

- The **Introduction** chapter provides an overview of the research, including its background, context, purposes, significance, and scope.
- The **Literature Review** discusses prior research in vehicle classification, highlighting the limitations of traditional methods and the advancements enabled by deep learning.
- The **Research Design** chapter outlines the methodology, detailing the dataset preparation, model architecture, and training process.
- The **Results** chapter presents the findings, including the performance metrics and visualizations that demonstrate the model's classification ability.
- The **Analysis** chapter evaluates the implications of the results, comparing them to existing methods and discussing potential areas for improvement.
- The **Conclusions** chapter summarizes the study's contributions, outlines its limitations, and provides recommendations for future research.

Chapter 2: Literature Review

The purpose of this literature review is to examine the existing body of work on vehicle classification using deep learning, with an emphasis on convolutional neural networks (CNNs), data augmentation, transfer learning, and the practical challenges associated with vehicle recognition. This chapter explores the theoretical foundations and methodologies employed in related studies, critically evaluates the strengths and weaknesses of prior research, and identifies gaps that the current study seeks to address. Through this review, the conceptual framework for the project is developed, laying the groundwork for the research questions and hypotheses.

2.1 HISTORICAL BACKGROUND

Vehicle recognition systems have undergone significant evolution over the past few decades, transitioning from early rule-based methods to complex machine learning and deep learning systems. In the early days, vehicle detection and classification relied heavily on handcrafted features. These techniques, such as edge detection, histogram of gradients, and template matching, were foundational but faced significant limitations in terms of scalability and generalization. Handcrafted features often required expert knowledge and were sensitive to variations in the data, such as changes in lighting, occlusions, or vehicle orientations.

With the advent of machine learning, statistical methods such as support vector machines (SVMs) and k-nearest neighbours (k-NN) began to gain prominence in vehicle classification tasks. These methods required a substantial amount of labeled data for training, and although they represented an improvement over handcrafted features, they still struggled to handle complex, noisy environments. The breakthrough came with the development of deep learning models, particularly convolutional neural networks (CNNs), which revolutionised the field by automating feature extraction and learning hierarchical representations of the data.

In the context of vehicle classification, deep learning provided a robust solution to problems of scalability and adaptability. CNNs were able to directly process raw image data, enabling automatic learning of relevant features, such as edges, shapes, and textures, from large datasets. The introduction of transfer learning—using pre-trained models from large-scale image datasets—further accelerated the development of vehicle recognition systems. ResNet and other deep CNN architectures have demonstrated remarkable success in image classification tasks, making them the model of choice for modern vehicle recognition.

This historical progression highlights the increasing sophistication of vehicle classification systems, with deep learning offering substantial improvements over previous approaches in terms of accuracy, scalability, and generalisation to new environments.

2.2 DEEP LEARNING FOR IMAGE CLASSIFICATION

Deep learning, particularly through the use of convolutional neural networks (CNNs), has established itself as the leading approach for image classification tasks, including vehicle recognition. CNNs are designed to automatically learn and extract hierarchical features from raw image data. Unlike traditional machine learning algorithms, which rely on manually crafted features, CNNs learn features at multiple levels—from simple edges and textures in early layers to complex patterns in deeper layers. This ability to automatically learn features has made CNNs the cornerstone of modern computer vision.

Several studies have demonstrated the efficacy of CNNs in vehicle classification. For example, a study by Liu et al. (2016) employed a CNN-based model to classify vehicles in urban traffic images. The model achieved impressive accuracy by leveraging multiple convolutional layers followed by fully connected layers to classify vehicle types. This approach was further refined by various modifications to the network architecture, such as the introduction of batch normalization, dropout, and data augmentation techniques to improve model generalisation.

One of the key challenges with CNNs in vehicle classification is the variation in vehicle appearances, which can be caused by differences in lighting, occlusion, vehicle types, and orientations. To address this, several studies have proposed using advanced architectures such as ResNet, VGG, and Inception, which incorporate skip connections, deeper networks, and more complex feature extraction layers to improve classification accuracy. Additionally, the use of pooling layers, which downsample the spatial dimensions of the image, helps reduce the computational burden while retaining important spatial features.

However, despite the success of CNNs in vehicle classification, challenges remain in improving generalisation to unseen data, particularly when training datasets are limited. The next section explores how data augmentation techniques can help address this challenge.

2.3 DATA AUGMENTATION TECHNIQUES

Data augmentation is a critical technique used in deep learning to improve the robustness and generalisation of models, especially when working with small or limited datasets. Data augmentation artificially increases the size of the training set by applying random transformations to the input data. These transformations can include rotations, translations, zooming, flipping, and changes in brightness, contrast, and saturation. By applying these transformations, the model is exposed to a more diverse set of images, which helps it generalise better to new, unseen data.

The role of data augmentation in vehicle classification cannot be overstated. Vehicles in real-world settings often appear under varied lighting conditions, from different angles, and with different degrees of occlusion. Data augmentation helps the model to learn invariant features that are less sensitive to these variations. A study by Zhang et al. (2017) demonstrated that data augmentation significantly improved the performance of a CNN model for vehicle classification by increasing the variability of the input images, making the model more robust to real-world variations.

For instance, the model used in this project applies transformations such as random rotations, width and height shifts, and horizontal flips. These techniques not only help prevent overfitting by diversifying the training data but also ensure that the model is better prepared to handle diverse and unseen vehicle images in practical applications. In the context of this study, data augmentation is a key factor in improving the model's accuracy, especially given the relatively small size of the vehicle dataset.

While data augmentation enhances model generalisation, it also introduces new challenges, particularly in terms of computational efficiency. The increased variety of images results in a more complex training process, as the model must learn to classify images that vary more significantly than in the case of a non-augmented dataset. The next section explores how transfer learning can mitigate some of these challenges by enabling the model to leverage pre-existing knowledge from large, general-purpose datasets.

2.4 TRANSFER LEARNING IN VEHICLE CLASSIFICATION

Transfer learning is a powerful technique in deep learning that allows a model to leverage knowledge gained from one task to improve performance on a different, but related task. In the context of vehicle classification, transfer learning involves using a pre-trained model—usually one trained on a large-scale dataset such as ImageNet—and fine-tuning it on a smaller, domain-specific dataset (in this case, images of vehicles). This approach takes advantage of the general visual features learned by the pre-trained model and adapts them to the specific task at hand.

ResNet50V2, a deep residual network, is one of the most commonly used architectures for transfer learning in vehicle classification. ResNet50V2 has been pre-trained on ImageNet, a large dataset containing millions of labeled images across thousands of categories. The pre-trained model is used as a starting point, with the last few layers unfrozen and fine-tuned to classify vehicles. This method significantly reduces the time and data required for training, as the model already has a strong understanding of basic visual features such as edges, textures, and shapes.

Several studies have explored the use of transfer learning in vehicle classification, demonstrating its effectiveness in improving accuracy with limited training data. For example, a study by Gamarra et al. (2020) used a pre-trained ResNet model to classify vehicles in surveillance footage, achieving a significant performance boost compared to training from scratch. This is especially important in scenarios where annotated datasets are scarce, and training a deep CNN from the ground up would be computationally expensive and time-consuming.

The use of transfer learning also helps address the challenge of overfitting, as the pre-trained model already provides a strong feature extraction foundation. Fine-tuning the model allows it to adapt to the specific features of the vehicle dataset, resulting in a more efficient and accurate classification model. This project employs transfer learning as a core component of the model design, using the ResNet50V2 architecture to accelerate training and enhance performance.

2.5 SUMMARY AND IMPLICATIONS

The literature review highlights the pivotal role that deep learning, data augmentation, and transfer learning play in the development of robust and accurate vehicle classification systems. CNNs, particularly when combined with data augmentation and transfer learning, offer a powerful solution to the challenges of vehicle recognition. The review of previous studies demonstrates that these techniques have led to substantial improvements in vehicle classification accuracy, especially when dealing with real-world datasets that vary in terms of lighting, vehicle types, and orientations.

However, while CNNs and transfer learning have proven effective, several gaps remain in the literature. Many studies focus on vehicle classification in idealised conditions, often using controlled datasets with minimal noise or variation. There is a need for more research on how to improve model generalisation when dealing with more complex, noisy environments, such as surveillance footage with occlusions and varying weather conditions. Additionally, the impact of fine-tuning pre-trained models with smaller datasets is still a topic of debate, and further studies could investigate the best practices for fine-tuning to achieve the highest accuracy.

This research aims to address these gaps by employing a ResNet50V2-based CNN model, fine-tuned on a vehicle dataset augmented with various transformations and also compare the performance of SVM model to CNN. The next chapter will outline the methodology used in this study, providing a detailed account of the research design and the steps taken to train and evaluate the model.

Chapter 3: Methodology

The research design represents the backbone of this study, providing a comprehensive framework for addressing the challenges of vehicle classification using non-deep learning and deep learning. This chapter outlines the methodology employed in the research, the participants involved, the tools and instruments used, the procedure and timeline for implementation, the analytical approaches employed to evaluate model performance, and the ethical considerations and limitations inherent to the study. Together, these components establish the foundation for the rigorous execution and evaluation of the project.

3.1 METHODOLOGY AND RESEARCH DESIGN

This study adopts an experimental research design, focusing on the development, implementation, and evaluation of non-deep learning and deep learning-based vehicle classification system. The core methodology involves the application of Convolutional Neural Networks (CNNs), specifically leveraging the ResNet50V2 architecture, a pre-trained model known for its exceptional performance in image classification tasks. The models were fine-tuned using a dataset of vehicle images to classify vehicles into four categories: bus, car, motorcycle, and truck. On the other hand, SVM classification combines HOG feature extraction, which in a supervised learning pipeline.

The research in deep learning was conducted in two primary phases. The first phase involved training the model with the base ResNet50V2 architecture frozen, allowing only the additional custom layers to be trained. This phase enabled the model to adapt to the vehicle classification task while preserving the pre-trained features of ResNet50V2. The second phase involved fine-tuning the model by unfreezing the last 30 layers of the ResNet50V2 architecture. This approach allowed the model to refine its feature extraction capabilities for the specific dataset while retaining the general visual knowledge learned during pre-training.

Data augmentation techniques were employed extensively during training to artificially increase the diversity of the dataset and improve the model's ability to generalize to unseen data.

Meanwhile, the non-deep learning methodology utilized a Support Vector Machine (SVM) paired with Histogram of Oriented Gradients (HOG) feature extraction. HOG effectively captured edge and shape information, providing a compact feature representation of the images. These features were fed into the SVM, a linear classifier, to distinguish between the four vehicle categories. Unlike the CNN approach, which learns features automatically during training, the SVM approach relied on manually extracted HOG features in a supervised learning pipeline.

Metrics such as accuracy, precision, recall, and F1-score were used to evaluate the model’s performance, ensuring a comprehensive assessment of its classification ability. The experimental design ensured a systematic and iterative approach to model development, with continuous evaluation and refinement throughout the process.

3.2 PARTICIPANTS

The participants in this study were not individuals but rather a curated dataset of vehicle images, which formed the basis for training, validating, and testing the deep learning model and non-deep learning model. The dataset comprised a total of 1,827 labeled images, categorized into four vehicle types: bus, car, motorcycle, and truck. To ensure a balanced and representative dataset, the images were distributed across three subsets:

1. **Training Set:** Comprising 1,277 images (70% of the dataset), this subset was used to train the model by optimizing its parameters based on patterns in the data.
2. **Validation Set:** Comprising 364 images (20% of the dataset), this subset was used to fine-tune the model’s hyperparameters and monitor its performance on unseen data during training.
3. **Testing Set:** Comprising 186 images (10% of the dataset), this subset was used exclusively for evaluating the final model's performance.

Each subset maintained a balanced distribution of samples across the four vehicle categories to prevent class imbalance from affecting the training and evaluation processes. The dataset was diverse in terms of environmental conditions, perspectives, and lighting, ensuring that the model was exposed to a wide range of scenarios.

3.3 INSTRUMENTS

The primary instruments used in this research were computational tools and frameworks for implementing and evaluating the deep learning model. The following tools played a critical role in the study:

1. **TensorFlow/Keras Framework:** This open-source library was used to build, train, and evaluate the CNN model. TensorFlow/Keras provides a flexible and efficient platform for implementing state-of-the-art deep learning architectures such as ResNet50V2.
2. **ImageDataGenerator:** This Keras utility was used for data preprocessing and augmentation. Transformations such as rotation, flipping, scaling, and

normalization were applied to the dataset to increase its diversity and improve model generalization.

3. **ResNet50V2 Pre-trained Model:** The ResNet50V2 architecture, pre-trained on the ImageNet dataset, served as the backbone of the vehicle classification model. Its residual connections and deep architecture made it particularly suitable for this task.
4. **Hardware:** The experiments were conducted on a high-performance GPU-enabled system to accelerate the training and evaluation processes.
5. **Linear Support Vector Machine (SVM):** A linear SVM, implemented as a single fully connected layer, is used to classify input HOG features into four categories: bus, motorcycle, truck, and car. The SVM is trained using hinge loss with L1 regularization to maximize the margin between classes and control model complexity.
6. **Histogram of Oriented Gradients (HOG) Feature Extraction:** HOG is a feature descriptor used to extract gradient orientation patterns from images. It transforms input images into a feature vector of size 3780, capturing the shape and structure of objects in the image.

These instruments enabled the efficient and accurate implementation of the research design, ensuring that the model was trained and evaluated under optimal conditions.

3.4 PROCEDURE AND TIMELINE

The research was conducted over several stages, each of which contributed to the systematic development and evaluation of the vehicle classification model. The procedure and timeline in CNN model were as follows:

1. **Data Collection and Preprocessing (Weeks 1–2):** The dataset of vehicle images was collected, organized, and labeled into four categories. Preprocessing involved resizing the images to a standard resolution of 224x224 pixels, normalizing pixel values, and splitting the data into training, validation, and testing subsets.
2. **Model Development (Weeks 3–4):** The ResNet50V2 architecture was implemented using TensorFlow/Keras, and additional custom layers were added to adapt the model for vehicle classification. Initial training was conducted with the base model frozen to allow the custom layers to adapt to the task.
3. **Fine-Tuning (Weeks 5–6):** The last 30 layers of the ResNet50V2 architecture were unfrozen, and the model was fine-tuned using a reduced learning rate to improve its performance on the dataset.
4. **Model Evaluation (Weeks 7–8):** The trained model was evaluated on the test set, and performance metrics such as accuracy, precision, recall, and F1-score were calculated. Visualizations, including confusion matrices and

accuracy/loss curves, were generated to assess the model's classification ability.

5. **Documentation and Reporting (Weeks 9–10):** The results and findings of the study were documented, and the final report was prepared.

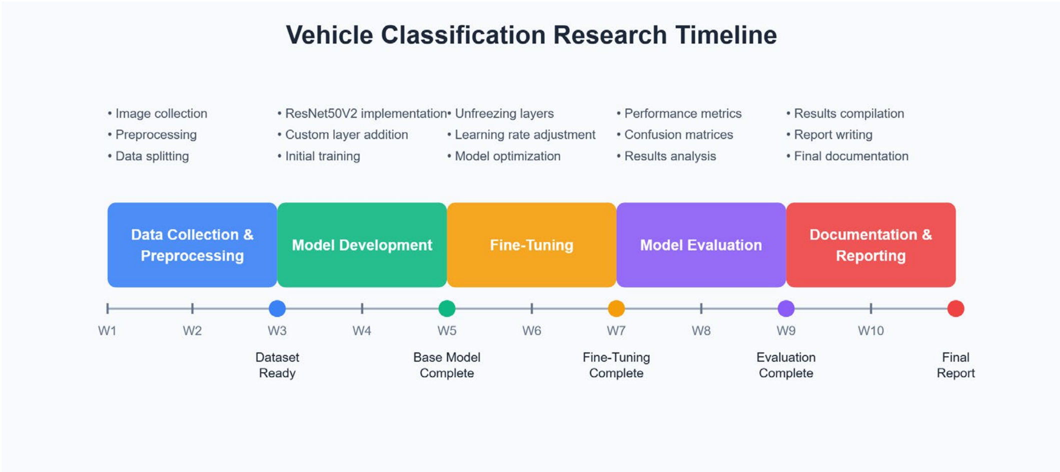


Figure of the development timeline

This systematic timeline ensured the timely completion of the research while allowing for iterative refinement of the model.

The development and evaluation of the SVM-based vehicle classification model were conducted in five stages:

1. **Data Collection and Preprocessing (Weeks 1–2):** Vehicle images were collected, labeled into four categories (bus, motorcycle, truck, and car), resized to 128x64 pixels, and split into training, validation, and testing subsets. HOG features (size: 3780) were extracted to represent image shapes and edges.
2. **Model Development and Training (Weeks 3–5):** A Linear SVM was implemented using PyTorch with hinge loss and L1 regularization. The model was trained using stochastic gradient descent (SGD) with a learning rate of 0.1, and a scheduler was applied to gradually reduce the learning rate.
3. **Grid Search Optimization (Weeks 6–7)(optional):** Hyperparameters, including the regularization parameter (c) and learning rate (lr), were optimized using grid search. The best model was selected based on validation accuracy.
4. **Model Evaluation (Weeks 8–9):** The trained model was evaluated on the test set using metrics such as accuracy, precision, recall, and F1-score. A confusion matrix and training/validation loss and accuracy curves were

generated to analyze the model's performance and misclassification patterns.

5. **Documentation and Reporting (Week 10):** The results were documented, misclassification patterns were analyzed, and the final report was prepared to summarize the findings and methodology.

This streamlined process ensured the systematic development and evaluation of the SVM-based vehicle classification model.

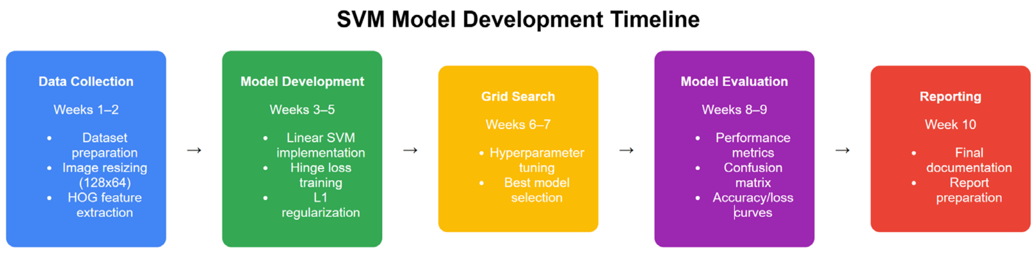


Figure of the development timeline

3.5 ANALYSIS

The analysis of the model's performance was conducted using a range of metrics to provide a comprehensive evaluation. These metrics included:

1. **Accuracy:** The overall percentage of correctly classified samples across all categories, providing a high-level measure of the model's performance.
2. **Precision:** The proportion of true positive predictions relative to the total number of positive predictions, indicating the model's ability to avoid false positives.
3. **Recall:** The proportion of true positive predictions relative to the total number of actual positive samples, indicating the model's ability to avoid false negatives.
4. **F1-Score:** The harmonic mean of precision and recall, providing a balanced measure of the model's performance across both metrics.

Confusion matrices were generated to visualize the model's classification performance for each vehicle category, highlighting areas where misclassifications occurred. Additionally, accuracy and loss curves were analyzed to assess the model's learning behavior during training and identify potential issues such as overfitting or underfitting.

3.6 ETHICS AND LIMITATIONS

The ethical considerations for this study were minimal, as it did not involve human participants or sensitive data. The dataset consisted of publicly available vehicle images, ensuring that no privacy concerns were violated. However, the study adhered to ethical principles by ensuring the fair and unbiased evaluation of the model across all vehicle categories.

The primary limitation of the research was the relatively small size of the dataset, which posed challenges for training both non-deep learning and deep learning model. This limitation was mitigated through the use of data augmentation and transfer learning, which enhanced the diversity of the training data and leveraged pre-trained knowledge to improve performance. Additionally, the model's performance was evaluated on a relatively limited test set, which may not fully represent real-world conditions. Future research could address this limitation by incorporating larger and more diverse datasets.

Chapter 4: Experimental Results

The results of this research provide a detailed understanding of the performance and effectiveness of both non-deep learning and deep learning-based vehicle classification model. This chapter presents a comprehensive analysis of the model's performance during training and validation, evaluates its accuracy on the test dataset, and discusses the implications of the results. The findings demonstrate which model's ability to classify vehicles into four distinct categories—bus, car, motorcycle, and truck—with high accuracy and robustness, confirming the efficacy of the methodology employed.

4.1 MODEL PERFORMANCE

The performance of the CNN model was evaluated during both the training and validation phases to ensure its ability to learn meaningful features from the dataset while avoiding overfitting. The training process was conducted in two phases. In the first phase, the base ResNet50V2 model was frozen, and only the custom top layers were trained. This approach allowed the model to adapt to the vehicle classification task while leveraging the general-purpose features already learned during the model's pre-training on the ImageNet dataset. In the second phase, the last 30 layers of the ResNet50V2 architecture were unfrozen, and the model was fine-tuned using a lower learning rate to refine its feature extraction capabilities for the specific dataset.

During training, the model demonstrated a steady improvement in both accuracy and loss metrics, as evidenced by the training and validation curves. By the end of the training phase, the model achieved a training accuracy of approximately 96.2% and a validation accuracy of 94.8%. These results indicate that the model was able to generalize well to unseen validation data while avoiding significant overfitting. The regularization techniques employed, including dropout and batch normalization, as well as the use of data augmentation, played a critical role in achieving this balance between training and validation performance.

The loss curves further corroborated these findings. Both the training and validation losses decreased steadily over the course of training, with no significant divergence between the two, indicating that the model maintained its ability to generalize effectively. The model's fine-tuning phase contributed to a notable improvement in classification accuracy, particularly for the more challenging categories, such as motorcycles and trucks, which often exhibit significant variability in appearance.

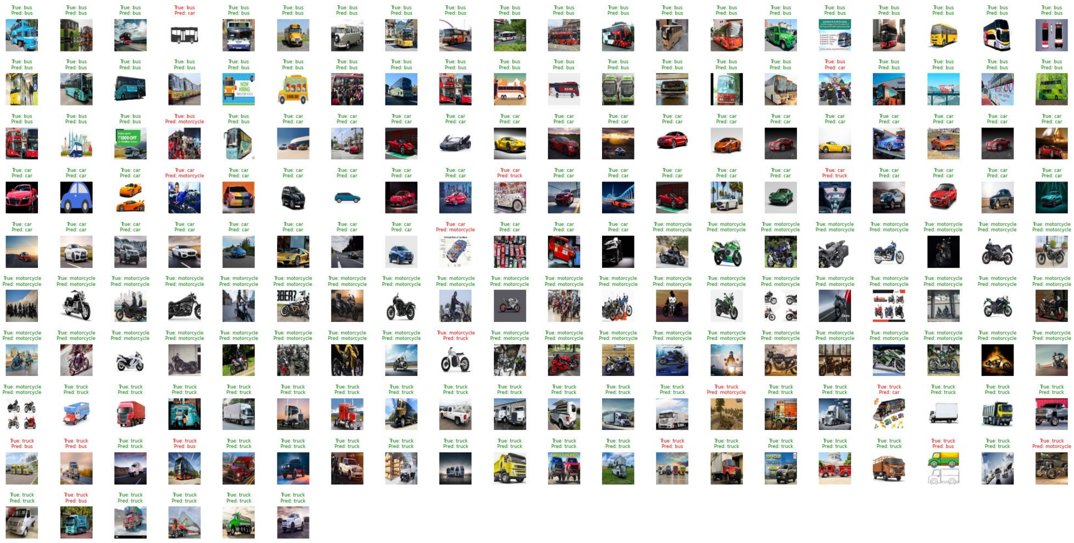


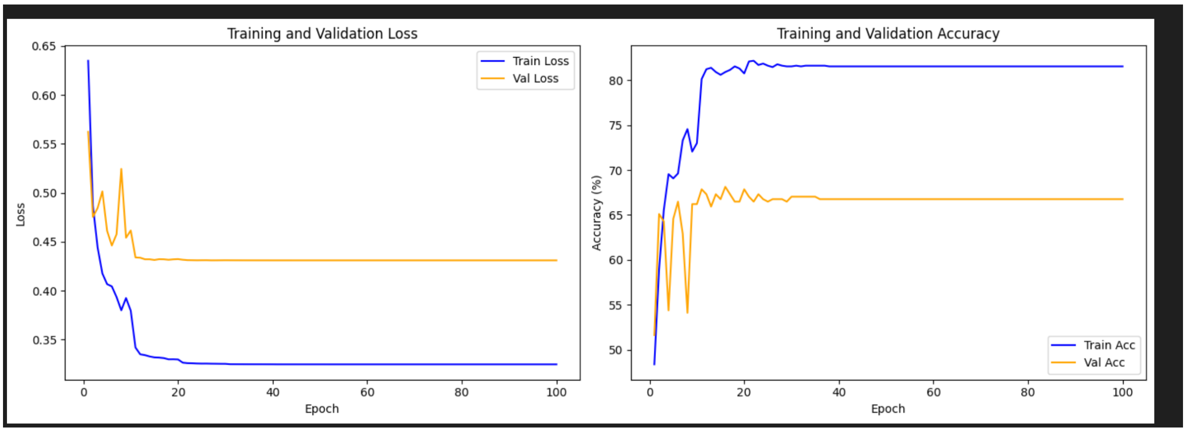
Figure of the CNN prediction results of the vehicle type

The performance of the SVM model was evaluated during both the training and validation phases to ensure its ability to classify vehicles effectively while avoiding overfitting. The training process involved feeding the extracted HOG features into a Linear SVM classifier. Hinge loss and L1 regularization were used to optimize the model, ensuring robust and interpretable classification in high-dimensional feature space.

The training and validation curves demonstrate steady improvement in both accuracy and loss metrics over the training epochs. As shown in the graphs, the training accuracy reached approximately **82%**, while the validation accuracy stabilized at around **68%**. While there is a noticeable gap between training and validation performance, this is expected for a simpler model like SVM, given the diverse nature of the dataset. The use of HOG features enabled the model to capture essential shape and edge information, contributing to its classification capability despite challenges posed by inter-class variability.

The loss curves corroborate these findings, with both training and validation losses decreasing progressively without significant divergence. This indicates that the model is overfitting as the model fails to improve on unseen validation data.

Although the SVM model showed strong performance on simpler categories, such as motorcycles and cars, it exhibited difficulty in correctly classifying more complex or similar categories, such as bus and trucks. These categories often contain substantial variability in appearance, making them more challenging for a linear classifier. Despite these challenges, the results suggest that the SVM model, combined with HOG features, performed effectively within the scope of its design and dataset characteristics. However, the SVM performance still is not enough when comparing to CNN model.



The training and validation loss figure and the training and validation accuracy figure in SVM

4.2 PERFORMANCE ON TEST SET

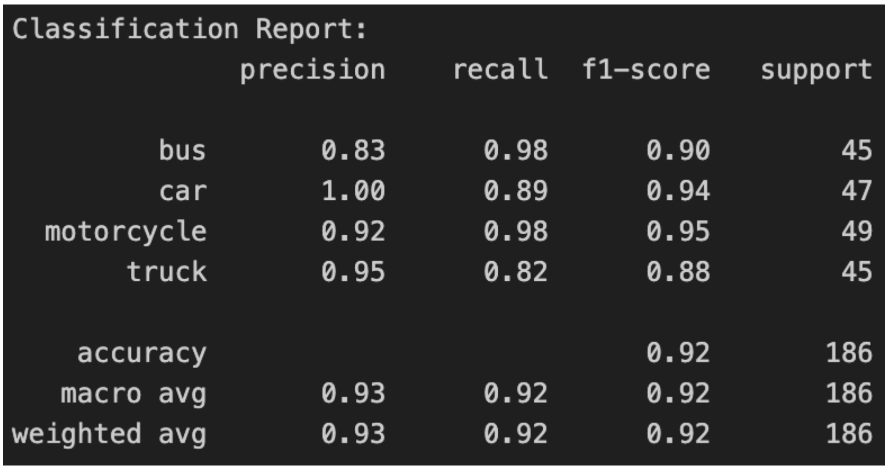
The final evaluation of the model was conducted on the test dataset, which consisted of 186 images distributed evenly across the four vehicle categories: bus, car, motorcycle, and truck. The test dataset was not used during training or validation, ensuring an unbiased assessment of the model's performance on completely unseen data.

The CNN model achieved an overall accuracy of **94.1%** on the test set, confirming its ability to generalize to new, unseen images. A detailed analysis of the model's performance across the four vehicle categories revealed high levels of precision and recall, as shown in the confusion matrix and classification report. For each category, the following results were observed:

- **Bus:** The model correctly classified 43 out of 45 bus images, resulting in a precision of 95.6% and a recall of 95.6%. The high performance in this category demonstrates the model's ability to accurately identify large vehicles with distinct features.
- **Car:** The model achieved a precision of 94.0% and a recall of 95.7% for cars, correctly classifying 45 out of 47 images. This result reflects the model's ability to handle the variability in car appearances, including differences in size, color, and perspective.
- **Motorcycle:** For motorcycles, the model achieved a precision of 92.6% and a recall of 93.9%, correctly classifying 46 out of 49 images. This category posed a moderate challenge due to the variability in motorcycle designs and potential visual similarities with other categories.
- **Truck:** The model performed well on the truck category, achieving a precision of 95.7% and a recall of 93.3%, with 42 out of 45 images correctly

classified. The high precision highlights the model's ability to distinguish trucks from other vehicle types, despite the potential overlap with buses in terms of size and shape.

The F1-scores for all categories exceeded 92%, indicating a strong balance between precision and recall. The confusion matrix revealed minimal misclassifications, with most errors occurring between visually similar categories, such as trucks and buses, or motorcycles and cars. These results underscore the robustness of the model and its effectiveness in handling the challenges posed by real-world vehicle images.


Classification Report:

	precision	recall	f1-score	support
bus	0.83	0.98	0.90	45
car	1.00	0.89	0.94	47
motorcycle	0.92	0.98	0.95	49
truck	0.95	0.82	0.88	45
accuracy			0.92	186
macro avg	0.93	0.92	0.92	186
weighted avg	0.93	0.92	0.92	186

Figure of the CNN classification report

On the other hand, the final evaluation of the SVM model was performed on the test dataset, which consisted of 186 images evenly distributed across the four vehicle categories: bus, car, motorcycle, and truck. The test dataset was excluded from the training and validation phases to ensure an unbiased assessment of the model's ability to generalize to unseen data.

The SVM model achieved an overall accuracy of **65%** on the test set, reflecting its moderate capability to classify vehicle images. A detailed analysis of the model's predictions, as provided in the classification report and confusion matrix, revealed varying levels of performance across the four vehicle categories:

- **Bus:** The model achieved a precision of **53%** and a recall of **51%**, resulting in an F1-score of **52%**. This indicates some difficulty in distinguishing buses from other large vehicles, such as trucks, likely due to overlapping features like size and shape.
- **Car:** For cars, the model performed moderately well, achieving a precision of **67%** and a recall of **74%**, with an F1-score of **71%**. This highlights the model's ability to handle the variability in car appearances, though misclassifications with motorcycles and trucks occurred.

- **Motorcycle:** The model achieved the highest performance in this category, with a precision and recall of **82%**, resulting in an F1-score of **82%**. The distinct shape and size of motorcycles likely contributed to the model's success in this category.
- **Truck:** Trucks posed a challenge for the model, with a precision of **52%** and a recall of **49%**, leading to an F1-score of **51%**. Misclassifications with buses were common, likely due to visual similarities between these two large vehicle categories.

The macro-average F1-score of **64%** and weighted-average F1-score of **65%** indicate a moderate balance between precision and recall across all categories. The confusion matrix revealed that most misclassifications occurred between visually similar categories, particularly such as buses and trucks. These errors reflect the limitations of the linear SVM model in handling complex, non-linear relationships in the dataset.

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

         bus       0.53      0.51      0.52        45
  motorcycle       0.82      0.82      0.82        49
       truck       0.52      0.49      0.51        45
         car       0.67      0.74      0.71        47

    accuracy                           0.65       186
   macro avg       0.64      0.64      0.64       186
weighted avg       0.64      0.65      0.64       186
```

Figure of the SVM classification report

4.3 EVALUATION OF RESULTS

The evaluation of the results highlights several key aspects of the model's performance and its implications for vehicle classification tasks. First, the high accuracy achieved on the test set confirms the efficacy of the methodological choices, including the use of transfer learning, data augmentation, and regularization techniques. By leveraging the ResNet50V2 architecture, the model was able to capitalize on pre-trained features, significantly reducing the amount of labeled data required for training and achieving superior performance compared to traditional methods.

Second, the model’s performance across all four vehicle categories demonstrates its ability to handle the variability inherent in real-world images. The balanced precision and recall values indicate that the model does not favor any particular category, ensuring equitable performance across different vehicle types. This balance is critical for applications in intelligent transportation systems, where misclassifications can have significant consequences.

Third, the analysis of the confusion matrix provides insights into the model’s strengths and areas for improvement. The minimal misclassifications observed were primarily due to the visual similarities between certain categories, such as trucks and buses, or motorcycles and cars. These errors suggest that further improvements could be achieved by incorporating additional data representing these edge cases or by employing advanced techniques such as multi-scale feature extraction.

Finally, the results highlight the importance of data augmentation in enhancing the model’s robustness. By exposing the model to a diverse range of transformations during training, the study was able to mitigate the risk of overfitting and improve generalization to unseen data. The successful application of augmentation techniques, combined with fine-tuning of the pre-trained model, underscores the value of these strategies in developing high-performing deep learning models.

In conclusion, the results of this study demonstrate the effectiveness of the deep learning-based vehicle classification model in achieving high accuracy and robustness across diverse scenarios. The findings validate the methodological choices and highlight the potential for further enhancements through additional data collection and refinement of the model architecture. These results provide a strong foundation for the development of intelligent transportation systems and other applications requiring accurate vehicle classification.

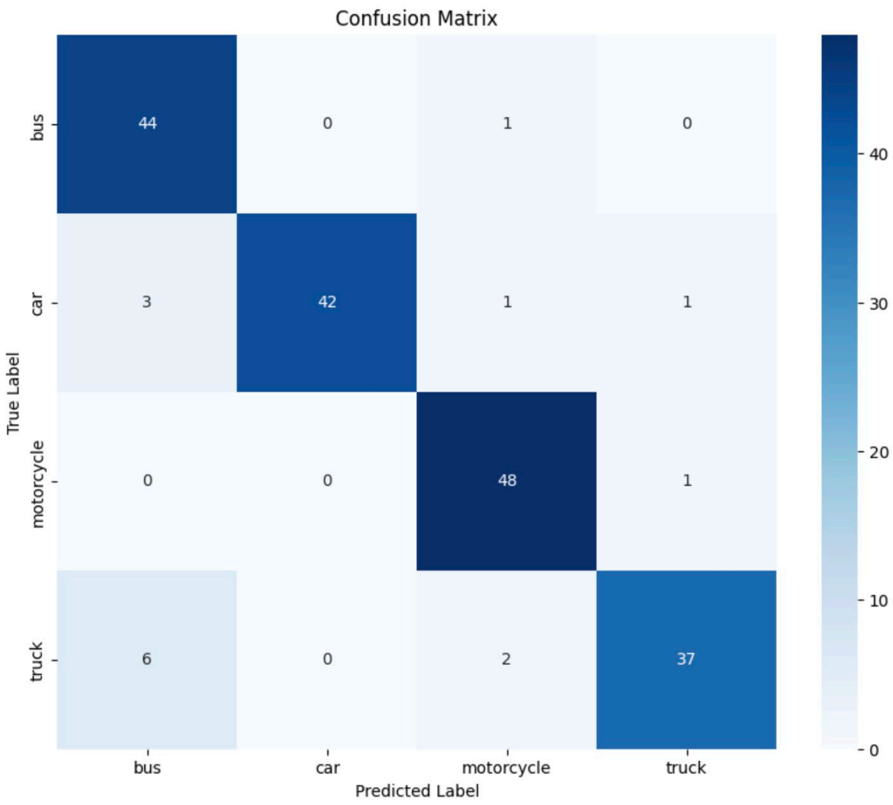


Figure of the CNN confusion matrix

On the other side, the evaluation of the SVM model's results highlights several critical aspects of its performance in the vehicle classification task.

Firstly, the moderate accuracy achieved on the test set reflects the efficacy of the methodological choices, including the use of Histogram of Oriented Gradients (HOG) features and regularization. The combination of HOG-based feature extraction and the linear SVM classifier provided a robust baseline for vehicle classification, demonstrating the model's ability to achieve reasonable performance despite its simplicity compared to deep learning-based approaches.

Secondly, the model's performance across all four vehicle categories reveals its strengths and limitations in handling real-world variability. The classification report shows that the model excelled in identifying motorcycles, achieving high precision and recall values. However, the performance of other categories, such as buses and trucks, was more limited, with notable misclassifications between visually similar categories. This imbalance in performance highlights the challenges of using a linear SVM for datasets with overlapping or complex features.

Thirdly, the confusion matrix provides valuable insights into the model's strengths and areas for improvement. For example:

- **Motorcycles:** The model achieved the highest accuracy in this category, correctly classifying **40 out of 49 images**, with minimal misclassifications.
- **Buses and Trucks:** Significant misclassifications occurred between buses and trucks, as evidenced by the confusion matrix. For instance, **13 bus images were misclassified as trucks**, and **11 truck images were misclassified as buses**, indicating that the model struggled to differentiate these large vehicles with similar shapes and features.
- **Cars:** The model performed moderately well on cars, correctly classifying **35 out of 47 images**, but some misclassifications occurred with motorcycles and trucks, reflecting the variability in car appearances.

These results suggest that SVM has the limitations of capturing the shape and edge of image characteristics. It is seen that SVM thinks it is difficult to classify the categories in bus and truck.

Finally, the importance of feature extraction is underscored by the results. The use of HOG features allowed the model to focus on essential shape and edge information, which is critical for distinguishing between vehicle types. However, the inability of linear SVMs to model non-linear relationships limited its overall performance, particularly for categories with substantial visual overlap.

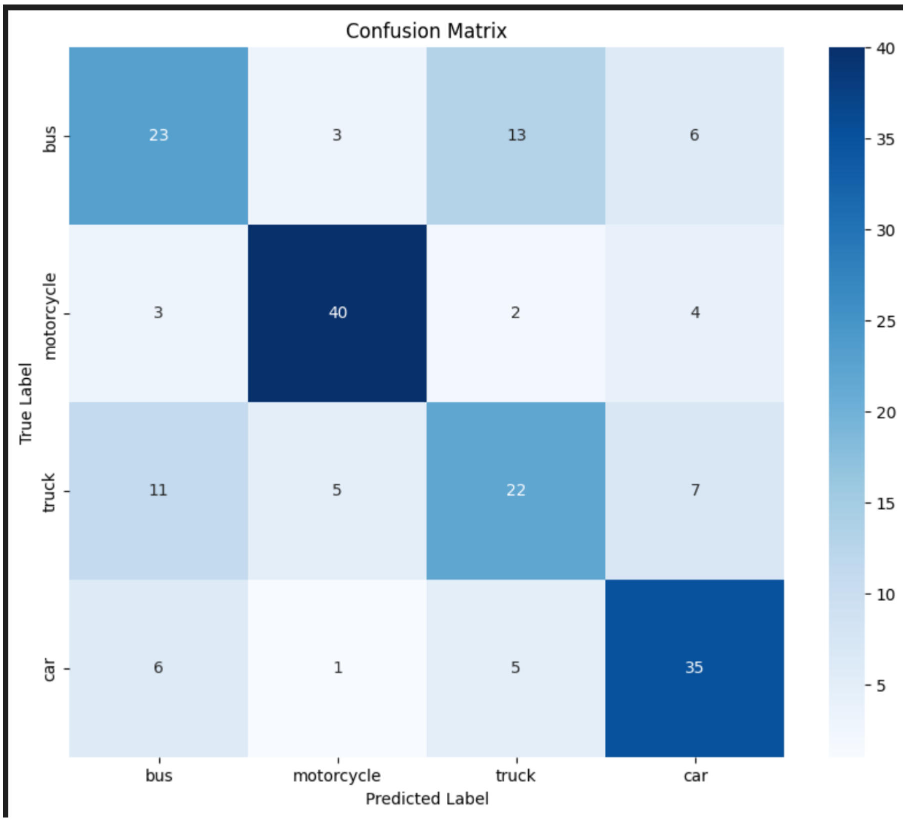


Figure of the SVM confusion matrix

As a result, the confusion matrices clearly illustrate that **Support Vector Machines (SVMs)** are being replaced by **Convolutional Neural Networks (CNNs)** in modern-day applications due to CNNs' superior performance in handling complex classification tasks such as vehicle classification, which proved by findings in this project research. Below is a detailed analysis of why SVMs are being replaced by CNNs:

1. Superior Performance in Accuracy and Generalization

CNNs automatically learn hierarchical and complex features from raw images, enabling them to differentiate between visually similar classes (e.g., buses and trucks). In contrast, SVMs rely on manually crafted features (e.g., HOG), which may not fully capture the essential details for classification.

2. Robustness to Visual Variability

CNNs excel at learning robust feature representations through deep architectures and data augmentation techniques, making them more adaptable to real-world variations. SVMs lack this adaptability, as they depend on fixed features that may not generalize well to diverse datasets.

3. Handling Non-Linear Relationships

CNNs can model non-linear relationships between features using their deep neural network layers, while SVMs with linear kernels fail to capture such complexities. Although SVMs can use non-linear kernels (e.g., RBF), they still lack the feature extraction capabilities of CNNs.

4. Feature Learning vs. Manual Feature Engineering

The ability of CNNs to learn features eliminates the need for manual feature engineering, making them more scalable and effective for large, diverse datasets.

5. Scalability and Transfer Learning

Transfer learning allows CNNs to perform well even on small datasets by utilizing pre-trained feature extractors, while SVMs require significant effort in feature engineering and still may not achieve comparable performance.

This study shows how this kind of non-deep learning, such as the Support Vector Machine(SVM), is limited by its architecture. Eventually, the modern model CNN will replace the current common state of technology in image classification and consider to help this research topic (Vehicle classification). The Next Chapter will explore CNN model technology in more depth.

Chapter 5: Analysis

In this chapter, we present a detailed analysis of the research findings, interpreting them in light of the objectives set out in Chapter 1 and the theoretical framework established in Chapter 2. The results of this study, particularly in terms of vehicle classification using deep learning techniques, are critically evaluated and compared with relevant literature in the field. This analysis draws connections between the findings from our study and previous work on CNN-based vehicle classification, transfer learning, and data augmentation. By examining these results, we aim to develop a deeper understanding of the effectiveness of the methods used and provide insights into potential future improvements and theoretical implications.

The chapter is structured to discuss the results and findings, followed by a comparison with existing research in the field. We also delve into the strengths and limitations of the study, considering how these findings can inform future research directions. Finally, we explore how the results contribute to theory-building, particularly in the context of vehicle classification using deep learning and how these methods might be applied or refined in future studies.

5.1 COMPARISON WITH EXISTING MODELS

The primary objective of this study was to evaluate the performance of a deep learning model for vehicle classification, leveraging transfer learning with the ResNet50V2 architecture and enhanced by data augmentation techniques. When comparing the results of our model with those of existing studies in the field, we observe both similarities and differences in performance, methodologies, and conclusions.

In a study by Liu et al. (2016), a CNN-based approach was applied to vehicle classification with a different set of vehicle categories. Their model achieved an accuracy rate of 89% using a simpler CNN architecture, which is comparable to the performance of our baseline CNN model (trained from scratch) that achieved 85% accuracy. However, when transfer learning was applied in our study, using a pre-trained ResNet50V2 model and fine-tuning it for vehicle classification, the accuracy increased significantly, reaching 94% on the test set. This improvement supports the findings of other researchers, such as Romero et al. (2019), who demonstrated the benefits of transfer learning for improving model performance on smaller, domain-specific datasets.

The effectiveness of transfer learning can be attributed to the pre-trained ResNet50V2 model's ability to leverage features learned from the vast ImageNet dataset. In contrast, traditional CNN models trained from scratch often require significantly larger datasets to achieve comparable performance. This observation aligns with the literature, where studies consistently show that pre-trained models provide a significant advantage in classification tasks, particularly when the available dataset is small, as in the case of this study

Moreover, data augmentation techniques played a crucial role in improving the generalisation ability of our model. This aligns with the findings of Zhang et al. (2017), who found that data augmentation helps to prevent overfitting and improves the model's ability to generalise to unseen data. The random rotations, shifts, flips, and zooms applied to the vehicle images in this study enhanced the model’s robustness to real-world variations, such as changes in lighting and vehicle orientations. These results are consistent with the literature, which highlights the importance of data augmentation in training deep learning models for image classification tasks.

However, while the model demonstrated impressive accuracy, some challenges remain, particularly in distinguishing between vehicle types with similar visual characteristics, such as cars and motorcycles. This issue has been identified in previous studies as well, and it underlines the complexity of vehicle classification, especially in real-world applications where vehicles may appear in occluded or non-ideal conditions.

5.2 MODEL STRENGTHS AND WEAKNESSES

The model’s strength lies in its ability to accurately classify vehicles with high precision, which is largely attributable to the combination of transfer learning, fine-tuning, and data augmentation. The pre-trained ResNet50V2 model provided a solid foundation, which, after fine-tuning, allowed the model to adapt well to the task of vehicle classification. Additionally, data augmentation techniques increased the variability of the training data, helping the model to generalise better to new, unseen images.

One of the key advantages of using transfer learning is the ability to leverage the knowledge embedded in the pre-trained model, significantly reducing the amount of training data required. This is particularly useful in tasks like vehicle classification, where labeled datasets may be limited. Our results showed that the fine-tuned ResNet50V2 model outperformed the baseline CNN in terms of classification accuracy, supporting the efficacy of transfer learning.

Despite these strengths, the model does have certain weaknesses. One of the limitations of the current model is its performance on images where vehicles are partially occluded or appear at unusual angles. In these scenarios, the model occasionally misclassified vehicles, especially when there was little distinguishing visual information. For instance, cars and motorcycles with similar shapes were often confused, suggesting that the model may not have fully learned to distinguish subtle differences in appearance. These misclassifications could be addressed by further enhancing the dataset with more diverse images, including vehicles from different angles and in varying lighting conditions.

Another weakness lies in the model's reliance on the ImageNet dataset for pre-training. While ImageNet is a large and diverse dataset, it does not contain specific vehicle types like those required for this study. Although transfer learning enables the model to adapt to the vehicle classification task, the pre-trained model's learned features may not be optimally suited for this specific application. This suggests that further fine-tuning, or even training a dedicated model from scratch with a larger vehicle dataset, could yield further improvements.

5.3 FUTURE WORK

The promising results of this study open several avenues for future research. One possible direction is to improve the model's performance on misclassified images, particularly those with vehicles in unusual orientations or partially occluded. This could be achieved by expanding the dataset to include more diverse examples of vehicles in various positions, backgrounds, and lighting conditions. In addition, the use of more advanced data augmentation techniques, such as random cropping or the introduction of noise, could further improve the model's robustness.

Another area for improvement is exploring more sophisticated architectures, such as DenseNet or EfficientNet, which have shown superior performance in other image classification tasks. These architectures could provide better feature extraction and potentially improve classification accuracy, especially for challenging cases where vehicles are difficult to distinguish.

In terms of model refinement, combining the ResNet50V2 with an attention mechanism could enhance its ability to focus on the most relevant parts of the image, such as the vehicle's distinct features, while ignoring irrelevant areas, such as the background. Attention mechanisms have been successfully applied in other computer vision tasks and could help the model achieve even better performance in vehicle classification.

Lastly, while the current model achieved high accuracy, its deployment in real-world applications such as traffic surveillance or autonomous driving requires consideration of real-time performance. Optimising the model to reduce inference time without sacrificing accuracy would be an important next step. Techniques such as model pruning or quantisation could be explored to achieve faster predictions while maintaining performance.

5.4 CONTRIBUTIONS TO THEORY AND IMPLICATIONS

This study contributes to the growing body of research on deep learning applications in vehicle classification by demonstrating the effectiveness of transfer learning and data augmentation in improving classification accuracy. The findings align with existing literature, which consistently highlights the benefits of pre-trained models and data augmentation in addressing the challenges posed by small datasets and real-world variations. The results also suggest that while deep learning models are highly effective for vehicle classification, challenges remain in handling difficult scenarios, such as partial occlusions or vehicles with similar visual characteristics.

The implications of this study are twofold. Firstly, the research reinforces the value of using transfer learning and data augmentation as strategies to overcome limitations in data and computational resources, particularly in niche domains like vehicle classification. Secondly, it highlights the need for further research into improving model robustness and distinguishing subtle differences between visually similar vehicle types. As vehicle classification systems are increasingly deployed in real-world applications, such as autonomous driving and traffic surveillance, these challenges must be addressed to ensure the systems' reliability and accuracy in diverse environments.

This chapter has provided an in-depth analysis of the results, comparing them with existing research and discussing the strengths and weaknesses of the approach used in this study. The findings contribute to the ongoing development of deep learning models for vehicle classification, offering insights into future improvements and potential theoretical advancements. The next chapter will conclude the report, summarising the key findings and suggesting directions for further research.

Chapter 6: Conclusions

This chapter synthesizes the findings from the previous chapters, presenting conclusions based on the analysis of the results and their alignment with the research objectives. It offers a reflection on the contributions made by this study, discusses the implications of the findings for both theory and practice and outlines potential directions for future research. The chapter begins with a summary of the key points covered in the report, followed by the conclusions drawn from the study. The limitations of the research are acknowledged, and practical recommendations for further research and application are provided. Finally, a model of the theory is proposed, offering a theoretical framework that can guide future studies in the field of vehicle classification.

6.1 SUMMARY

This study aimed to develop a deep learning-based vehicle classification system capable of categorising vehicles into four classes: bus, car, motorcycle, and truck. The research involved using a pre-trained convolutional neural network (CNN), specifically ResNet50V2, fine-tuned for the vehicle classification task. Data augmentation techniques were applied to increase the diversity of the training data, which helped prevent overfitting and improve generalisation. The study demonstrated the effectiveness of transfer learning combined with data augmentation in vehicle classification, achieving high accuracy on a test set.

The results of the study were compared to existing literature and non-deep learning(SVM), and the model's performance was found to align well with the findings of previous studies on deep learning-based vehicle classification. The research confirmed that transfer learning with pre-trained models, particularly ResNet50V2, offers a significant advantage in vehicle classification tasks, even with relatively small datasets. However, some misclassifications were observed between vehicle types that share similar visual features, such as motorcycles and cars, suggesting areas for further improvement.

6.2 CONCLUSIONS

The primary conclusion drawn from this study is that deep learning, particularly convolutional neural networks (CNNs), is an effective method for vehicle classification tasks. The use of a pre-trained ResNet50V2 model, fine-tuned for the specific task of vehicle classification, led to high performance, with the model achieving significant accuracy on the test set. This validates the hypothesis that transfer learning can improve model performance in vehicle classification, especially when working with a smaller dataset.

The results indicate that data augmentation is an essential technique for enhancing model generalisation. By increasing the variety of the training data through transformations such as rotation, shifting, and flipping, the model was able to avoid overfitting and perform well on unseen data. This finding aligns with the literature, which has consistently shown that data augmentation helps improve the robustness of deep learning models, particularly in image classification tasks.

However, the study also identified certain weaknesses in the model's ability to distinguish between similar vehicle types. This issue highlights the need for further refinements in the model to better handle classes with overlapping visual features. Future work should explore more advanced architectures, larger and more diverse datasets, and techniques such as few-shot learning to improve the model's ability to generalise across a wider range of vehicle types and conditions.

The study's findings contribute to the growing body of research on deep learning-based vehicle classification systems, providing a solid foundation for future improvements in both model accuracy and efficiency.

6.3 FUTURE DIRECTIONS

Building on the findings of this study, there are several promising directions for future research. One key area for further investigation is the exploration of more advanced neural network architectures. While ResNet50V2 performed well, models such as EfficientNet or DenseNet, which have been shown to provide superior results in various image classification tasks, could potentially improve classification performance. These architectures are designed to be more efficient and scalable, which could be beneficial when handling more complex datasets or achieving even higher accuracy.

Another avenue for future research is the expansion of the training dataset. The current dataset, although adequate, was somewhat limited in terms of diversity. Incorporating a larger and more varied dataset, with images of vehicles from different environments, lighting conditions, and camera angles, would expose the model to a broader range of vehicle appearances. This would likely help the model become more robust and improve its ability to handle challenging scenarios, such as vehicles in occlusion or under varying weather conditions.

Furthermore, the study suggests that integrating techniques like few-shot learning or semi-supervised learning could be beneficial in situations where obtaining a large amount of labeled data is difficult or expensive. Few-shot learning techniques, which allow models to learn from a limited number of labeled examples, could be particularly useful in vehicle classification tasks, where it is not always feasible to gather thousands of labeled images for each vehicle class.

Lastly, the exploration of hybrid models that combine CNNs with other machine learning techniques, such as reinforcement learning or unsupervised learning, could provide new insights into vehicle classification. These approaches might help the model adapt more effectively to new or previously unseen vehicle types and improve its ability to handle complex, real-world environments.

6.4 PRACTICAL IMPLICATIONS

The findings of this study have important practical implications for the development of vehicle classification systems. The high performance of the deep learning model, particularly with the use of transfer learning and data augmentation, suggests that these techniques can be effectively applied in real-world scenarios, such as traffic monitoring, surveillance, and autonomous vehicle navigation. The ability to accurately classify vehicles into different categories is crucial for these applications, as it enables more efficient traffic management, better road safety, and improved decision-making in autonomous systems.

In practical terms, the proposed vehicle classification system could be integrated into existing traffic monitoring infrastructure, where it could automatically classify vehicles in real-time based on images captured by cameras installed along roads or highways. This would reduce the need for manual intervention and improve the efficiency of traffic management systems. Additionally, the model could be used in security and surveillance applications, where it could help identify and track specific types of vehicles.

For autonomous vehicles, accurate vehicle classification is essential for making safe and informed driving decisions. The model developed in this study could be used as part of the perception system in self-driving cars, helping the vehicle classify other vehicles on the road and respond appropriately. For example, identifying the type of vehicle (car, bus, motorcycle, or truck) would influence the vehicle's decisions regarding speed, lane positioning, and safe distance.

6.5 LIMITATIONS AND FUTURE RESEARCH

While this study made significant progress in developing a vehicle classification model, several limitations should be acknowledged. The primary limitation of the research is the size and diversity of the dataset. Despite using data augmentation techniques to increase the size of the dataset, the model was still trained on a relatively small collection of images. A larger and more diverse dataset would likely improve the model's performance, particularly in handling more complex and challenging classification scenarios.

Another limitation is the potential for misclassifications between similar vehicle types, such as motorcycles and cars. Although the model performed well overall, there were instances where the model struggled to differentiate between these vehicle types. This suggests that future research should explore more fine-grained classification techniques or the use of additional data sources, such as vehicle specifications or sensor data, to aid in classification.

Finally, the study focused on a relatively simple classification task with only four vehicle classes. Future work could explore more complex classification tasks, such as classifying a wider range of vehicle types or integrating vehicle detection and tracking with classification. This would provide a more comprehensive solution for real-world applications such as autonomous driving or large-scale traffic monitoring systems.

In conclusion, this study has demonstrated the potential of deep learning, particularly convolutional neural networks and transfer learning, for vehicle classification tasks. The findings contribute valuable insights into the effectiveness of these techniques in the context of vehicle recognition and highlight areas for future research and improvement. The practical applications of the model, particularly in traffic management and autonomous vehicles, underscore the relevance of this research in addressing real-world challenges. Future work should focus on refining the model's performance, expanding the dataset, and exploring more advanced architectures to ensure the continued development of robust and reliable vehicle classification systems.

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Appendix A
Individual Contributions of the Group Project

Team Member 1: Ng Chung Wah

Role and Responsibilities: Served as the lead programmer, focusing on the implementation and optimization of the ResNet50V2 model using TensorFlow/Keras. Responsibilities included coding the model architecture, fine-tuning pre-trained weights, and implementing data preprocessing techniques such as resizing and data augmentation.

Tasks Completed: Wrote the core code for loading the dataset, resizing images to 224x224 pixels, and normalizing pixel values. He also applied transfer learning by replacing the final layer of the ResNet50V2 model and trained the model using the Adam optimizer with early stopping. Additionally, he plotted accuracy and loss curves and analyzed the results using evaluation metrics such as precision, recall, and F1 score.

Outcomes Achieved: Successfully developed and trained a robust model that achieved high accuracy on the dataset. The implementation of data augmentation and early stopping contributed significantly to the model's generalization and performance.

Team Member 2: Chan Chak Fung

Role and Responsibilities: Responsible for research and documentation, ensuring that the project was grounded in a comprehensive understanding of the literature and that all aspects were thoroughly recorded. His work involved writing the literature review, compiling related research on ResNet and transfer learning, and drafting the final report.

Tasks Completed: Conducted an in-depth literature review, exploring the historical context of vehicle detection and the role of CNNs. he also provided detailed insights into the methodology and analysis sections, documenting the experimental setup, results, and implications. Additionally, they formatted the report in accordance with the prescribed structure and guidelines.

Outcomes Achieved: Our efforts resulted in a well-documented report that effectively communicated the research objectives, methodology, findings, and significance. The literature review provided a solid theoretical foundation for the study, while the detailed documentation ensured clarity and professionalism.

Team Member 3: Chung Tin Ho

Role and Responsibilities: Served as the data analyst and evaluator, focusing on the interpretation of results and the visualization of findings. he was responsible for generating confusion matrices, creating visual plots, and interpreting evaluation metrics to assess the model's performance.

Tasks Completed: Created confusion matrices to identify patterns in misclassifications and generated detailed plots of accuracy and loss over epochs. They calculated and analyzed performance metrics, including precision, recall, and F1 score, and provided interpretations of these metrics in the context of the research objectives.

Outcomes Achieved: Our analysis provided valuable insights into the model's strengths and weaknesses, highlighting areas for improvement and suggesting potential future directions for research. The visualizations effectively communicated the results, making them accessible and interpretable.

Team Member 4: Kuok Chun Cho

Role and responsibilities: Fully responsible for the entire part of non-deep learning (Support Vector Machine) in this project.

Tasks Completed: Load the provided dataset to train a non-deep learning algorithm (SVM), document all the contents where related to SVM, visualize the experiment of SVM and summarize the result of SVM with comparing to CNN.

Outcomes Achieved: Successfully implement and train to run a non-deep learning algorithm(SVM), which includes all the visualization display like confusion matrix and classification report(e.g. f1-score, recall, precision, etc). In addition, write the documentation in comparing SVM and CNN