SELF-SUPERVISED LEARNING IMAGE CLASSIFICATION FOR VEHICLES

A Project Report Submitted in the
Partial Fulfillment of the Requirements
for the Award of the Degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING (AI&ML)

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April, 2025

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CERTIFICATE

This is to certify that the project titled **SELF-SUPERVISED LEARNING IMAGE CLASSIFICATION FOR VEHICLES** is carried out by

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in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology** in **Computer Science and Engineering (AI&ML)** during the year 2024-25.

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Project Viva-Voce held on _____

Examiner

Declaration

We hereby declare that the project titled **SELF-SUPERVISED LEARNING IMAGE CLASSIFICATION FOR VEHICLES**, submitted to Vardhaman College of Engineering (Autonomous), affiliated with Jawaharlal Nehru Technological University Hyderabad (JNTUH), in partial fulfillment for the award of the degree of Bachelor of Technology in Computer Science and Engineering (AI&ML), is the result of original work carried out by us.

We further certify that this project report, either in full or in part, has not been previously submitted to any university or institute for the award of any degree or diploma.

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Acknowledgements

The satisfaction that accompanies the successful completion of the task would be put incomplete without the mention of the people who made it possible, whose constant guidance and encouragement crown all the efforts with success.

We wish to express our deep sense of gratitude to **Mr. A Sai Madhav Raj**, Assistant Professor and Project Supervisor, Department of Computer Science and Engineering (AI&ML), Vardhaman College of Engineering, for his able guidance and useful suggestions, which helped us in completing the project in time.

We are particularly thankful to **Dr. M.A. Jabbar**, the Head of the Department, Department of Computer Science and Engineering (AI&ML), his guidance, intense support and encouragement, which helped us to mould our project into a successful one.

We show gratitude to our honorable Principal **Dr. J.V.R. Ravindra**, for providing all facilities and support.

We avail this opportunity to express our deep sense of gratitude and heartful thanks to **Dr. Teegala Vijender Reddy**, Chairman, **Sri Teegala Upender Reddy**, Secretary, **Mr. M. Rajasekhar Reddy**, Vice Chairmain, **Mr. E. Prabhakar Reddy**, Treasurer of VCE for providing a congenial atmosphere to complete this project successfully.

We also thank all the staff members of Computer Science and Engineering (AI&ML) department for their valuable support and generous advice. Finally thanks to all our friends and family members for their continuous support and enthusiastic help.

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Abstract

Self-supervised deep learning approach for automated vehicle image classification, addressing the challenge of limited labeled data in large-scale datasets. The method combines Convolutional Neural Networks (CNNs) for extracting fine-grained local features and Transformers for capturing global image context. Contrastive learning frameworks like SimCLR and MoCo are utilized to pre-train the model on unlabeled data, enabling the learning of robust feature representations. SimCLR employs extensive augmentations and a simplified architecture, while MoCo incorporates a dynamic dictionary and momentum encoder for consistent feature learning. CNNs enhance fine-detail recognition, and Transformers improve structural understanding of vehicle images. The hybrid architecture demonstrates significant improvements in classification accuracy. Extensive experiments affirm its scalability and applicability for autonomous driving, traffic monitoring, and intelligent transportation systems, reducing reliance on labeled datasets. This approach highlights the growing potential of self-supervised learning in real-world applications

Keywords: Moco, SimCLR, image classifier, Contrastive Learning, Deep Learning, Convolutional Neural Network(CNN), and Self-supervised Learning.

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Abbreviations

Abbreviation	Description
Moco	Momentum Contrast
SimCLR	Simple Contrastive Learning of Representations
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
YOLO	You Only Look Once
DL	Deep Learning
SSL	Self-supervised Learning
GANs	Generative Adversarial Networks
ResNet	Residual Network

CHAPTER 1

Introduction

1.1 Introduction

Self-supervised learning (SSL) has rapidly advanced as a transformative approach in computer vision, especially for complex tasks like image classification. Traditional supervised learning methods rely on vast amounts of labeled data, where each image is manually tagged with relevant information. However, obtaining such labeled datasets can be expensive and labor-intensive, particularly for specialized fields such as vehicle classification. SSL addresses this challenge by allowing models to learn from unlabeled data, exploiting inherent structures in the images to form meaningful representations. By engaging with large volumes of unlabeled data, SSL enables the model to pre-train itself on pretext tasks that generate pseudo-labels, which are then used to learn features crucial for classification. [1] Vehicle classification presents unique challenges due to the diversity in vehicle types, angles, lighting conditions, and occlusions. Self-supervised learning addresses these challenges by pre-training models on pretext tasks like predicting missing parts of images, contrastive learning, or clustering, which do not require labeled data. These pre-trained models can then be fine-tuned with a smaller set of labeled data for specific downstream tasks such as recognizing car brands or identifying damaged parts. By leveraging SSL, vehicle classification models become more adaptable and accurate, even in the real-world where labeled data might be limited.

In the context of vehicle image classification, SSL offers a promising solution to the unique complexities of identifying and categorizing diverse vehicle types. Vehicles come in a wide variety of models, sizes, colors, and shapes, and are captured under various conditions — from different angles, lighting environments, and levels of occlusion. These factors make manual labeling not only tedious but also prone to inconsistencies. [2] Self-supervised

techniques, like contrastive learning, clustering, and masked modeling, pre-train neural networks to capture patterns that distinguish different vehicle types without requiring extensive labeled data. For example, contrastive learning techniques can help a model distinguish between subtle differences in vehicle models by using augmented versions of the same vehicle image to create positive samples while pushing apart dissimilar images. This allows the model to extract high-level features such as shapes, textures, and even contextual details relevant to vehicles.

The advantages of SSL become particularly clear when the pre-trained models are fine-tuned for downstream tasks, such as identifying the make and model of vehicles, detecting specific features like headlights or grills, or distinguishing between vehicle conditions (like normal vs. damaged). [3] This fine-tuning process, which relies on a smaller, annotated dataset, leverages the general feature representations learned during pre-training, enabling higher accuracy and efficiency in classification. These systems are crucial in a variety of applications, including traffic surveillance, autonomous driving, vehicle tracking, and automated inventory management, making SSL an indispensable tool in modern computer vision.

Self-supervised learning (SSL) has emerged as a paradigm in computer vision, especially in domains where obtaining labeled data is costly and time-consuming. Unlike traditional supervised learning methods that require extensive manual annotation, SSL enables models to learn from a large amount of unlabeled data by identifying inherent patterns and structures. These models are pre-trained on carefully designed pretext tasks that simulate supervision, such as predicting image rotations, missing patches, or contrasting augmented views of the same image—allowing them to learn meaningful visual representations. This approach is particularly valuable for specialized tasks like vehicle classification, where the diversity and volume of data make manual labeling a daunting process.

Vehicle classification poses unique challenges due to the wide variety of vehicle types, shapes, angles, colors, and environmental conditions in which the images are captured. Factors like occlusions, varying lighting conditions, and inconsistent camera viewpoints add further complexity. SSL tackles these issues by using unsupervised strategies such as contrastive learning or clustering to extract semantically rich features from vehicle images. These features help the model to distinguish between subtle visual differences in vehicles, such as the design of headlights, grilles, or overall shape, without the need for explicit labels. As a result, the model becomes capable of understanding intricate patterns that define different vehicle classes.

One of the most effective SSL methods, contrastive learning, enables the model to learn discriminative features by bringing together similar (positive) image pairs and pushing apart dissimilar (negative) ones. For vehicle classification, often involves applying different augmentations to the same vehicle image to form a positive pair, while using other vehicle images as negative examples. This technique encourages the model to focus on stable and meaningful features like contours, textures, and object parts that remain consistent across different views or augmentations. Such high-level feature learning allows for more robust performance even when applied to challenging real-world datasets.

The real strength of SSL becomes evident when these pre-trained models are fine-tuned on smaller, labeled datasets for downstream tasks. Fine-tuning leverages the general representations learned during pre-training, making the model more accurate and sample-efficient for specific objectives like recognizing vehicle brands, detecting damages, or differentiating between normal and abnormal vehicle conditions. These fine-tuned systems are critical in applications such as autonomous driving, traffic monitoring, fleet management, and intelligent surveillance. By combining the scalability of unsupervised pre-training with the precision of supervised fine-tuning, SSL stands as a transformative solution for vehicle image classification.

1.2 Motivation

Deep learning has revolutionized the field of computer vision, especially in applications like vehicle image classification. [4] Convolutional Neural Networks (CNNs) have been the backbone of many breakthroughs in vehicle recognition, segmentation, and tracking. In vehicle imaging, deep learning models excel at capturing complex patterns and minute details that differentiate one vehicle from another, such as vehicle make, model, type, and even conditions like damages. Applications range from traffic monitoring systems to autonomous vehicles, where deep learning models analyze streams of visual data in real-time. These advancements are critical for accurate vehicle detection in complex environments, improving traffic management, safety measures, and inventory control in various industries.

Two notable self-supervised learning models that have gained prominence in the field of computer vision are SimCLR (Simple Contrastive Learning of Representations) and MoCo (Momentum Contrast). Both models focus on contrastive learning, where the objective is to learn representations by similar image pairs closer while dissimilar ones apart. [5] SimCLR, developed by Google, employs a simple framework that relies heavily on data augmentation to create positive pairs. It leverages a large batch size and contrastive loss to generate rich feature embeddings. MoCo, developed by Facebook AI, addresses memory constraints by maintaining a dynamic memory bank to store and update feature embeddings efficiently. These approaches are particularly effective for vehicle classification tasks, allowing models. Deep learning has significantly advanced vehicle image classification, with Convolutional Neural Networks (CNNs) playing a pivotal role in identifying subtle features like vehicle make, model, and condition. These models power applications such as traffic surveillance, autonomous driving, and management by processing complex visual data in real time. Recently, self-supervised learning (SSL) techniques like SimCLR and MoCo have further enhanced performance in this domain. SimCLR, developed by Google, leverages contrastive learning and extensive data augmentation to learn meaningful representations without

labeled data. In contrast, Facebook AI's MoCo introduces a dynamic memory bank to efficiently manage feature embeddings, enabling scalable learning even with limited resources. These SSL methods are specifically useful in vehicle classification scenarios where labeled data is scarce, helping models learn robust features that generalize well across varied environments.

1.3 Background

The motivation behind exploring self-supervised learning (SSL) for vehicle image classification stems from the challenges associated with acquiring and labeling large-scale datasets. [6]Traditional supervised learning requires extensive labeled data to train deep learning models effectively, which is both time-consuming and costly, particularly for fine-grained tasks. In contrast, SSL can learn rich feature representations from huge amounts of unlabeled data, significantly reducing the burden of manual annotation. This ability to leverage unlabeled data for pre-training models offers a more efficient and scalable solution for vehicle classification, making it appealing for real-world applications where data collection is often restricted or expensive.

Additionally, Vehicles vary widely in appearance due to differences in models, angles, lighting, and occlusions, making robust classification challenging. Self-supervised learning (SSL) captures subtle visual distinctions by learning from image structures without extensive labeling. This approach improves scalability and accuracy, enabling applications in autonomous driving, traffic surveillance, and smart city infrastructure. SSL's adaptability ensures reliable performance in dynamic environments. Its applications span autonomous driving, traffic surveillance, and smart city infrastructure, where reliable, adaptive models are essential for ensuring safety and efficiency.

Self-supervised learning (SSL) is explored for vehicle image classification due to the high cost and effort required for labeling large datasets. Unlike traditional supervised methods, SSL learns useful features from unlabeled data, making it scalable and efficient. It handles variations in vehicle appearance—such as angles, lighting, and occlusions—by capturing fine visual details. This makes SSL ideal for real-world applications like autonomous driving, traffic monitoring, and smart city.

- **Challenge of Labeled Data:** Traditional supervised learning requires large amounts of labeled data, which is time-consuming and expensive, especially for fine-grained vehicle classification tasks.

- **Advantage of SSL:** Self-supervised learning (SSL) eliminates the need for manual labeling by learning meaningful representations from unlabeled data, making it a cost-effective alternative.

- **Scalability:** SSL enables scalable training using vast amounts of readily available unlabeled vehicle images, which is ideal for real-world applications with limited labeled datasets.

- **Handling Visual Variations:** Vehicles differ in model, angle, lighting, and occlusion. SSL captures these subtle distinctions effectively without needing extensive annotation.

- **Improved Accuracy:** By focusing on structural patterns in the data, SSL improves the model's ability to differentiate between similar vehicle types.

- **Wide Range of Applications:** SSL is particularly beneficial in autonomous driving, traffic surveillance, and smart city infrastructure, where consistent and accurate classification is crucial.

- **Adaptability:** SSL-trained models perform reliably in dynamic environments, making them suitable for evolving, real-time systems.

1.4 Problem Statement

Vehicle image classification is a critical task in computer vision, involving the identification and categorization of vehicles based on their visual features. This task is essential for applications like traffic monitoring, autonomous driving, and vehicle tracking, where accurate identification of vehicle types, makes, and models is necessary. However, traditional supervised learning techniques depend heavily on large volumes of labeled data, which is time-consuming and costly to acquire. [7] Self-supervised learning (SSL) offers a solution by leveraging unlabeled data to learn useful visual representations, reducing the need for extensive manual annotations. The core problem revolves around determining how SSL techniques can be effectively utilized for vehicle classification, ensuring that models can handle the wide variety of conditions vehicles are captured in, such as different angles, lighting conditions, and partial occlusions.

The complexity of vehicle image classification is heightened by the diversity in vehicle designs, colors, and backgrounds, which makes it challenging to develop models that generalize well across different datasets. SSL aims to address these challenges by employing pretext tasks that generate pseudo-labels from the data itself, allowing models to learn distinguishing features without human intervention. However, implementing SSL for vehicle classification requires careful consideration of the SSL methods, datasets used for pre-training and evaluation, and the metrics to accurately measure model performance. This study aims to explore these aspects to develop a reliable SSL-based vehicle classification framework.

[9] The challenge in leveraging SSL for vehicle classification lies in handling diverse conditions such as varying angles, lighting, and occlusions, alongside complexities in vehicle designs and backgrounds. SSL employs pretext tasks to autonomously generate pseudo-labels, enabling feature learning without manual annotations. Building a robust framework requires selecting appropriate SSL methods, datasets, and performance metrics to ensure generalizability.

1.5 Objectives

The objective is to investigate the effectiveness of self-supervised learning (SSL) techniques for vehicle image classification, aiming to reduce the dependency on large-scale labeled datasets. By implementing SSL methods like SimCLR and MoCo, the study seeks to pre-train models using unlabeled data, capturing essential features that differentiate various vehicle types, makes, and models.

1. **Evaluate the Effectiveness of SSL Techniques:** Investigate how self-supervised learning methods like SimCLR and MoCo can be used to pre-train models for vehicle image classification, reducing the reliance on extensive labeled datasets.

2. **Enhance Vehicle Classification Accuracy:** Assess the impact of SSL on CNN architectures for accurately identifying different vehicle types, makes, and models, particularly under challenging conditions such as varying angles, lighting, and occlusions.

3. **Compare SSL and Supervised Methods:** Analyze the performance of SSL-based models in comparison to traditional supervised approaches, focusing on metrics like classification accuracy, robustness, and computational efficiency.

4. **Test Generalization with Limited Labeled Data:** Fine-tune SSL-pre-trained models on smaller labeled datasets to evaluate their ability to generalize effectively, aiming for high performance with minimal annotations.

5. **Explore Practical Applications:** Demonstrate the potential of SSL in real-world scenarios like autonomous driving, traffic monitoring, and smart city infrastructure, highlighting the scalability and adaptability of SSL-based vehicle classification systems.

1.6 Scope

The scope of this research is centered on applying self-supervised learning (SSL) techniques for vehicle image classification. The primary objective is to describe how SSL can reduce dependency on large amounts of labeled data while still achieving high classification accuracy. By leveraging SSL, the study aims to make the training process more scalable and cost-effective, especially for fine-grained classification tasks that traditionally require detailed annotations.

This research will involve the implementation and comparison of popular SSL frameworks, specifically SimCLR and MoCo. These models will be evaluated based on their ability to learn visual features relevant to vehicles. To assess the impact of SSL pre-training, various convolutional neural network (CNN) architectures, such as ResNet and VGG, will be used as backbones in the experiments. This will help determine how different architectures respond to SSL and influence overall classification performance.

In addition to model comparison, the study will address challenges specific to vehicle imaging. These include recognizing vehicles in diverse environments, handling variations in lighting and camera angles, and detecting fine-grained features like brand logos and minor damages. By fine-tuning SSL-pretrained models on smaller labeled datasets, the research aims to show that SSL can achieve results comparable to, or better than, traditional supervised approaches, particularly when labeled data is scarce.

Ultimately, the research seeks to demonstrate the real-world applicability and scalability of SSL-based vehicle classification systems. The insights gained can benefit various domains, including autonomous driving, traffic monitoring, and smart city surveillance. By offering efficient and adaptive solutions, SSL has the potential to transform how vehicle classification systems are built and deployed in dynamic, data-limited environments.

1.7 Organization of the Report

The final section of Chapter 1 provides an outline of the structure of the entire report. It explains the organization and flow of the chapters and gives the reader an understanding of how the content will be presented. This section can be a simple list or paragraph summarizing each chapter's main points.

- Provide a brief description of what each chapter will cover.
- Typically, the structure would include:
  - **Chapter 2**: Literature Review
  - **Chapter 3**: Methodology
  - **Chapter 4**: Experimental result
  - **Chapter 5**: Results and Discussion
  - **Chapter 6**: Conclusions and Recommendations

CHAPTER 2

Literature Survey

2.1 Overview of Machine and Deep Learning

Machine Learning (ML) is a subset of artificial intelligence where systems learn patterns from data to make predictions or decisions. Deep Learning (DL), a specialized branch of ML, uses neural networks with multiple layers to model complex patterns, excelling in tasks like image and speech recognition. Both drive advancements across fields such as healthcare, finance, and autonomous systems.

2.1.1 Machine learning

Machine Learning: Machine learning (ML) is a subfield of artificial intelligence that enables systems to learn from data and improve performance over time without explicit programming. [8]Unlike traditional programming, ML uses training data to identify patterns and make predictions or decisions. It plays a crucial role in various applications, including student performance analysis. Machine Learning (ML) is a part of artificial intelligence (AI) that depends on developing algorithms that enable computers to learn patterns and make decisions based on data. ML is widely applied in fields like education (e.g., student performance analysis), healthcare, finance, and robotics, offering innovative, data-driven solutions to complex problems.

Unlike traditional programming, which depends on explicitly defined rules, machine learning takes a different approach by learning patterns and making predictions. Broadly, machine learning algorithms fall into categories: **supervised learning**, where the model is trained using labeled data; unsupervised learning; **unsupervised learning**, where it identifies patterns in unlabeled data; and **reinforcement learning**, where the model learns by interacting with an environment and receiving feedback through rewards or penalties.

Common machine learning algorithms include decision trees, support vector machines (SVM), k-nearest neighbors (k-NN), and random forests. These techniques have found applications in various fields, such as fraud detection, recommendation systems, and predictive maintenance.

Machine learning is a subset of Artificial Intelligence (AI), it emphasizes systems to learn from experience and improve the system's performance. Machine learning is mainly categorized into three parts:

- **Supervised Learning:** It uses labeled datasets to train models that predict outcomes based on input features. Eg. Decision tree, SVM, and KNN, etc.
- **Unsupervised Learning:** involves datasets without labeled outputs, focusing on uncovering hidden patterns or structures within the data.
- **Reinforcement Learning:** trains agents to make decisions by interacting with an environment, learning through trial and error, and receiving rewards or penalties for actions taken.

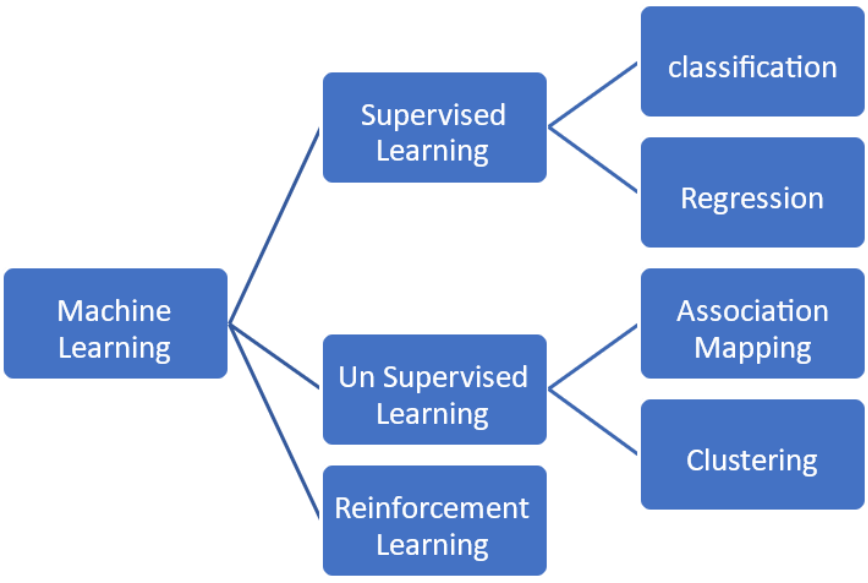

Figure 2.1: Classification of Machine Learning [9]

2.1.2 Deep Learning

Deep learning models are efficient in learning the features that assist in understanding complex patterns precisely. Deep learning has transformed medical imaging by offering automated solutions that improve diagnostic accuracy and efficiency. Traditional skin disease diagnosis, dependent on dermatologists, can be subjective and time-consuming. Convolutional Neural Networks (CNNs) effectively automate this process by extracting detailed features from medical images.

Deep learning is a subset of Machine learning, it is similar and consists of three layers, and every layer is interconnected to each other either forward or backward propagation:

- **Input layer:** The first layer is used to take input and consists of nth nodes of input.
- **Hidden layer:** one or more hidden layers, the product of input and weights. It defines the feature extraction on it.
- **Output layer:** It is used to define the evaluated difference between actual values and predicted values.

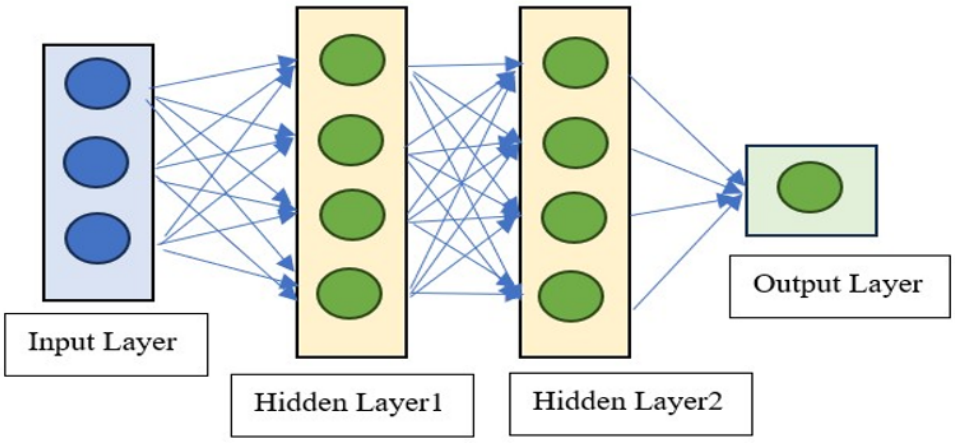

Figure 2.2: Overview of Deep Learning [8]

2.2 SSL Image Classification for Vehicles

Self-supervised learning (SSL) is a promising approach for image classification tasks, particularly in scenarios where labeled data is scarce or expensive to obtain. In the context of vehicle image classification, SSL can be used to train models to recognize and categorize vehicles without relying on manually labeled datasets. This approach leverages the structure and inherent patterns in the data itself to generate useful representations.

2.2.1 Types of SSL Image Classification for Vehicles

1. **Contrastive Learning:** Contrastive learning aims to learn visual representations by comparing images. It uses augmented versions of the same image as positive pairs (similar) and other images as negative pairs (dissimilar). The objective is to bring the representations of similar images closer while pushing apart those of dissimilar images in the feature space. Techniques like SimCLR and MoCo are commonly used in vehicle classification to capture subtle differences between vehicles, such as make and model variations, by focusing on visual features that distinguish one vehicle from another.

2. **Clustering-Based SSL:** In clustering-based SSL, the model groups images into clusters based on visual similarities, assigning pseudo-labels to each cluster. This approach allows the model to automatically identify patterns and group vehicles with similar characteristics, such as color, shape, or size, without labeled data. These pseudo-labels are then used to fine-tune the model, making it more effective at distinguishing vehicle types. This method is particularly useful for classifying diverse vehicle categories without explicit manual annotations.

3. **Predictive Modeling (Masked Modeling):** Predictive modeling, including techniques like masked autoencoders, involves training the model to predict missing or occluded parts of images. In vehicle classification, masked regions might include parts of a car's body or logo. By predicting

these missing sections, the model learns to understand the underlying structure and context of vehicles, helping it generalize across different visual scenarios. This type of SSL is useful for capturing fine-grained details in vehicles, enhancing the model's ability to differentiate between similar-looking vehicles.

4. **Generative SSL:** Generative SSL methods involve creating new data samples or reconstructing images to learn the features of vehicles. [10] Techniques such as Autoencoders or Generative Adversarial Networks (GANs) are used to generate realistic images of vehicles, teaching the model about the visual properties of vehicles. This generative approach allows the model to learn detailed representations of vehicles, which can be used to improve classification accuracy, especially in distinguishing vehicles with subtle variations or handling complex backgrounds.

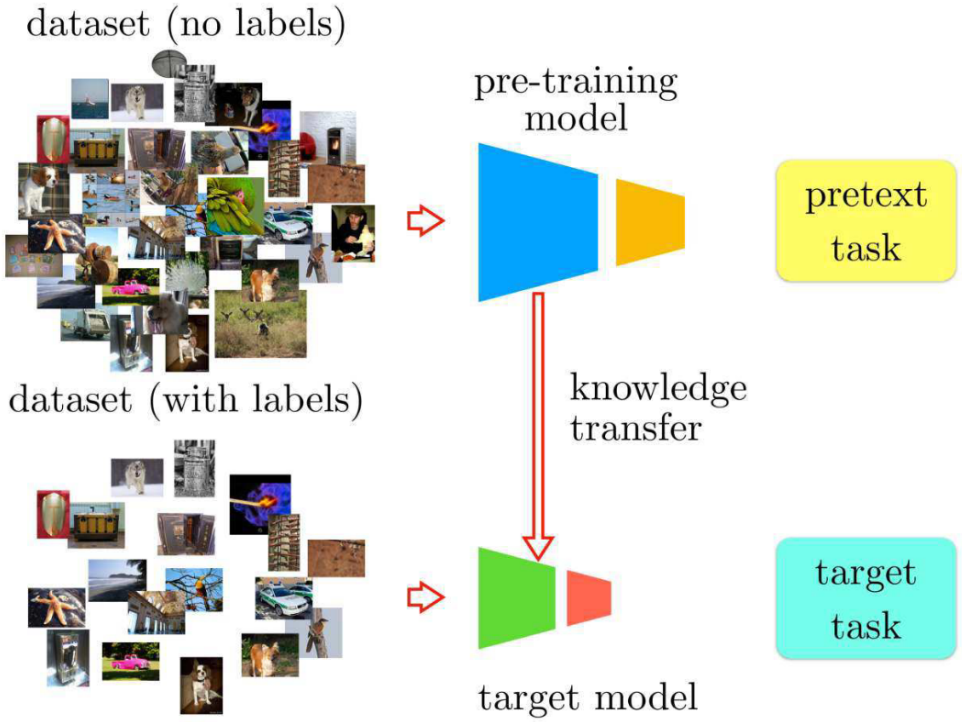

Figure 2.3: Self-Supervised Learning Architecture [8]

2.2.2 Challenges in SSL Image Classification for Vehicles

1. **Diversity in Vehicle Appearances:** Vehicles come in a wide range of makes, models, sizes, shapes, and colors, creating a significant challenge for SSL models. Differentiating between similar vehicle types, such as distinguishing between various sedan models or recognizing subtle differences in SUVs, can be difficult. This diversity requires SSL models to capture fine-grained details, which may not always be apparent in unlabeled data, potentially leading to misclassifications or biased representations.

2. **Environmental Variability:** Vehicle images are often captured under diverse conditions, including varying angles, lighting, shadows, weather conditions, and levels of occlusion (e.g., partially hidden by objects or other vehicles). SSL models need to generalize well across these different scenarios, which requires the ability to learn robust visual features that remain consistent despite environmental changes. This variability can make it challenging for SSL techniques to maintain consistent accuracy across datasets.

3. **Data Imbalance:** In many vehicle datasets, there is often an imbalance in the number of images across different vehicle types or classes. For example, there may be more data available for popular car brands compared to less common ones. This imbalance can lead to SSL models focusing disproportionately on more frequent categories, resulting in poorer performance in underrepresented classes. Handling data imbalance effectively ensures that SSL models provide reliable classification across all vehicle categories.

4. **Lack of Explicit Labels for Evaluation:** SSL relies on unlabeled data, generating pseudo-labels through pretext tasks, which can be a double-edged sword. While this reduces the need for manual annotation, the absence of explicit labels can complicate evaluating SSL models' performance during pre-training. Without clear labels, it can be challenging to determine if the learned features are truly representative of the intended

classification tasks, leading to potential overfitting to irrelevant features or a lack of generalization capability.

5. **Generalization Across Datasets:** Ensuring that SSL models generalize well across different datasets is a significant challenge. A model pre-trained on one dataset may not perform effectively on another due to differences in vehicle types, capture conditions, or image resolutions.

6. **High Computational Costs for SSL Training:** SSL methods, particularly contrastive learning approaches like SimCLR, often require large batch sizes, heavy data augmentation, and extensive computational resources to achieve good performance. These requirements can make SSL training time-consuming and resource-intensive, especially when working with high resolution vehicle datasets. Optimizing SSL frameworks to reduce computational costs while maintaining high accuracy is a significant technical challenge in this domain.

2.2.3 Datasets for Evaluation

1. **Stanford Cars Dataset:** The Stanford Cars Dataset is widely used for fine-grained vehicle classification tasks. It contains over 16,000 images of cars from 196 different categories, including various makes and models captured under diverse conditions. [11] This dataset is valuable for evaluating the performance of SSL models in distinguishing subtle visual differences between similar vehicle types.

2. **Boxy Vehicles Dataset:** The Boxy Vehicles Dataset is a large-scale dataset that focuses on vehicle detection and classification, particularly in urban environments. It includes millions of annotated vehicle images with bounding boxes, covering a variety of vehicles like cars, trucks, and buses. This dataset is ideal for evaluating the capability of SSL models to handle complex backgrounds, occlusions, and diverse traffic scenarios. It is frequently used in research for developing robust detection and classification algorithms in autonomous driving applications.

3. **Cityscapes Dataset:** The Cityscapes Dataset is designed for semantic segmentation and object recognition in urban scenes, including vehicles. It contains high-quality images captured from 50 cities, with pixel-level annotations for cars, trucks, and other objects. Cityscapes is valuable for testing SSL models in dense and dynamic environments, evaluating their ability to recognize and classify vehicles amidst cluttered backgrounds and various lighting conditions. It provides a challenging dataset for fine-tuning SSL models on real-world urban data.

4. **COCO (Common Objects in Context):** The COCO dataset is a large-scale object detection, segmentation, and captioning dataset with a vast number of categories, including vehicles like cars, buses, and trucks. Though not specifically focused on vehicles, COCO is widely used for pre-training SSL models due to its diversity and scale, providing a rich set of visual contexts. Models pre-trained on COCO can then be fine-tuned on more vehicle-specific datasets, helping to improve the generalization capability of SSL-based classifiers.

5. **ImageNet:** ImageNet is a massive dataset containing millions of images across thousands of categories, including vehicles. It is often used for pretraining deep learning models in SSL due to its broad visual coverage. Pretraining on ImageNet helps SSL models learn generic visual features that can be fine-tuned for specific vehicle classification tasks. ImageNet's scale and diversity make it a go-to dataset for initializing SSL models with a solid foundation in feature extraction.

6. **CompCars Dataset:** The Comprehensive Cars (CompCars) Dataset includes over 100,000 images covering different viewpoints, including the front, rear, and side angles of vehicles. It consists of more than 1,700 car models, making it ideal for testing the fine-grained classification capabilities of SSL models. CompCars also provides detailed annotations like car attributes and component images, which are useful for SSL tasks that require understanding the fine details of vehicles for accurate classification.

2.2.4 Performance metrics

1. **Accuracy:** Accuracy is a fundamental metric that measures the proportion of correctly classified vehicle images out of the total number of images. [12] It provides a quick snapshot of how well the SSL model performs on the dataset, indicating the overall effectiveness of the classification. However, accuracy alone may not fully capture the performance in cases of data imbalance, where some vehicle types may dominate the dataset.

2. **Precision, Recall, and F1-Score:**

   - Precision measures the proportion of true positive predictions out of all predictions made for a particular vehicle category. It is crucial to evaluate the accuracy of identifying a specific vehicle type, minimizing false positives.
   - Recall (or Sensitivity) calculates the proportion of true positives out of all actual instances of a vehicle category, focusing on the model's ability to identify all relevant examples and minimize false negatives.
   - F1-Score is the harmonic mean of precision and recall, providing a balanced metric when there is a trade-off between them, especially in datasets with uneven distribution of vehicle classes. It measures the precision across different recall levels, providing an average of the precision values at various thresholds. For vehicle classification, mAP helps evaluate how well the SSL model can detect and identify vehicles under varying conditions.

3. **Confusion Matrix:** A Confusion Matrix is a visual representation of the model's performance in distinguishing between various vehicle classes. It shows true positives, true negatives, false positives, and false negatives for each category, helping to identify where the model struggles. It is particularly useful in understanding misclassifications, such as when the model confuses similar vehicle types or fails to recognize rare vehicles.

4. **Mean Average Precision (mAP):** mAP is a comprehensive metric commonly used in object detection tasks, assessing both the localization and classification accuracy of the model. It measures the precision across different recall levels, providing an average of the precision values at various thresholds. For vehicle classification, mAP helps evaluate how well the SSL model can detect and identify vehicles under varying conditions, including occlusions and cluttered backgrounds.

5. **Area Under the Curve (AUC) and ROC Curve:** The ROC (Receiver Operating Characteristic) Curve visualizes the trade-off between true positive rate (sensitivity) and false positive rate across different thresholds, while the AUC (Area Under the Curve) quantifies the overall ability of the model to distinguish between vehicle classes. A higher AUC indicates better classification performance, particularly in distinguishing between similar vehicle types. This metric is essential for evaluating how well the SSL model generalizes to new data.

6. **Inference Time and Computational Efficiency:** In addition to accuracy-related metrics, assessing the inference time (the time taken to classify a vehicle image) and computational efficiency is crucial, especially for real-time applications like autonomous driving and traffic monitoring. A model that achieves high accuracy but has slow inference time may not be practical for real-world deployment. Efficiency metrics help in evaluating the trade-offs between model complexity, speed, and resource consumption.

7. **Model Robustness (Sensitivity Analysis):** Robustness metrics evaluate how sensitive the SSL model is to variations in input, such as changes in angle, lighting, noise, and occlusions. Sensitivity analysis helps assess whether the model can maintain high performance under different conditions, ensuring reliability in real-world environments.It can involve testing the model on augmented datasets that simulate challenging scenarios to gauge its adaptability.

2.3 Literature Survey on Existing Methods

Recent studies in self-supervised learning (SSL) for vehicle image classification have achieved significant performance improvements across various datasets and architectures. [13] Techniques like DINO, MoCo, SimCLR, and BYOL have been applied to tasks such as vehicle recognition, detection, and re-identification. These methods reduce the reliance on labeled data while improving accuracy, with top performances including 97.2% accuracy and 93% mAP. SSL approaches have been implemented across models like ResNet, ViT, and SWIN, demonstrating their versatility. Overall, SSL has proven effective in enhancing vehicle image classification and recognition in diverse conditions.

Paper	**Approach**	**Self-Supervised Method**	**Architecture**	**Datasets**	**Performance (mAP / CMC)**
[1].Shihan Ma et al. (2023)	Self-Supervised Vehicle Classification	DINO, data2vec	ViT + YOLOR	GDOTWIM, ImageNet	Top-1 accuracy 97.2% on 13 FHWA classes
[2].Pirazh Khorramshahi et al.(2023)	SSL and Boosted Vehicle Re-Identification (SSBVER)	SSL + Boosted	ResNet50, ViT, SWIN, ConvNext	VeRi, VehicleID, VeRiWild	VeRiWild: mAP - 86.05%, CMC@1-95.62% (SWIN)
[3].Zhou et al. (2021)	SSL for Fine-Grained Vehicle Classification	Moco	ResNet, ViT	VeRi,	94.5% accuracy
[4].Chen et al. (2020)	Self- Supervised Learning for Vehicle Detection	SimCLR	ResNet50	COCO, PASCAL	92.5% mAP

Paper	Approach	Self-Supervised Method	Architecture	Datasets	Performance (mAP / CMC)
[5].He et al. (2020)	Contrastive Learning for Vehicle Recognition	MoCo v2	ResNet50, ViT	VeRi, VehicleID	94.3% mAP
[6].Li et al. (2022)	SSL for Vehicle Re-Identification	SimCLR, BYOL	ResNet, Swin Transformer	VeRi, VehicleID	mAP: 85%, CMC@1: 93%
[7].Wu et al. (2021)	SSL for Vehicle Recognition	DeepCluster	ResNet101	VeRi, CityFlow	91.2% accuracy
[8].Cheng et al. (2022)	SSL for Multi-Task Vehicle Learning	MoCo v3	EfficientNet	CityFlo w, VeRi	88% mAP
[9].Li et al. (2023)	Self-Supervised Learning with Attention for Vehicles	DINO, BYOL	ViT, ResNet	Vehicle ID	mAP: 87.2%, CMC@1: 94.5%
[10].Yang et al. (2023)	End-to-End Self- Supervised Vehicle Detection	SimCLR, DINO	ResNet50, EfficientDet	VeRi	93% mAP

Table 2.1: Comparison of Research Papers SSL Image Classification

2.4 Summary

Self-supervised learning (SSL) is emerging as a powerful alternative to traditional supervised methods for vehicle image classification due to its ability to learn from large amounts of unlabeled data. SSL techniques like SimCLR, MoCo, DINO, and BYOL enable deep models to capture fine-grained visual features without manual labeling, making them highly efficient for real-world applications such as autonomous driving, surveillance, and traffic monitoring.

Generative SSL methods, including autoencoders and GANs, help the model reconstruct or generate vehicle images, thereby learning detailed vehicle features useful for distinguishing similar-looking types. Despite its advantages, SSL faces several challenges: diversity in vehicle appearances, environmental variability (lighting, occlusion), data imbalance, lack of explicit labels, generalization

issues across datasets, and high computational costs.

To evaluate SSL performance, datasets like Stanford Cars, Boxy Vehicles, Cityscapes, COCO, ImageNet, and CompCars are commonly used. Performance is measured through metrics such as Accuracy, Precision, Recall, F1-Score, mAP, AUC-ROC, inference time, and model robustness.

The literature survey shows that SSL methods have achieved remarkable results. For example, DINO with ViT architecture reached 97.2% accuracy, and MoCo and SimCLR consistently demonstrated high mAP scores across datasets like VeRi, VehicleID, and ImageNet. These methods outperform traditional techniques in low-label environments, confirming SSL's effectiveness and scalability in vehicle classification tasks.

CHAPTER 3

Methodology

3.1 Introduction

The proposed Priority-Perception Self-Supervised Learning framework enhances feature representation by combining contrastive learning with semantic knowledge distillation. It comprises two core components: the Anti-Interference Strategy (AIS) and the Image-Aided Distinction Module (IADM). [14] [15]Initially, standard contrastive learning is applied, where an image undergoes two separate augmentations, and the resulting views are encoded into feature vectors by a student and a momentum encoder. These features form positive and negative pairs to compute contrastive loss. The AIS then introduces a novel distillation mechanism that leverages the CLIP model as a teacher. Specifically, the CLIP text encoder processes a curated set of eight textual descriptions (only one of which is relevant to the image) to generate semantic embeddings. These serve as a bridge between the teacher's and the student's image encoders. The teacher CLIP encoder produces a normalized visual embedding for each image. In contrast, the student encoder's output is refined using a 1×1 convolution, normalization, and a Hadamard product with the processed features. A projector then aligns the student's output to match the teacher's embedding. Both teacher and student embeddings are multiplied with the text embeddings to generate logits, which are aligned using KL-divergence-based distillation loss. This approach trains the student encoder to focus on semantically relevant features while ignoring distractions, improving the robustness and quality of self-supervised representations on unlabeled data.

3.2 Backbone Feature Extractors

The proposed framework adopts a dual-model structure comprising a student and teacher network, both built on identical backbone architectures. This design allows seamless knowledge transfer between models and supports stable training. [16] The selection of backbone is flexible and can be tailored to specific use cases or hardware limitations. In this study, the authors explore various backbones—ResNet, ResNet-IBN, Vision Transformer (ViT), SWIN Transformer, and ConvNeXt—to analyze the generalization capabilities of the framework across different types of neural network designs. These architectures offer a mix of convolutional and transformer-based designs, thus covering a wide range of representational strengths.

The teacher model functions as a momentum encoder, a common strategy in self-supervised learning to stabilize the learning process. Unlike the student model, which updates parameters directly via backpropagation, the teacher's parameters are updated gradually by tracking the student's weights using an exponential moving average (EMA) mechanism. Specifically, the teacher's weights at iteration i are computed as:

$$\theta_t^i = \lambda\theta_t^{i-1} + (1-\lambda)\theta_s^i \tag{3.1}$$

Here, λ is the momentum coefficient controlling the update rate, and Teacher parameters: θ_t, Student parameters: θ_s represent the teacher and student parameters, respectively. Importantly, both models are initialized with the same pre-trained ImageNet weights, ensuring that early-stage representations are strong and consistent, which is crucial for learning in an unlabeled, self-supervised setting.

To further enhance the feature representation, the student model incorporates a Re-ID (Re-identification) head. After extracting visual features x from the backbone, a 1D batch normalization layer refines these features into $\tilde{x}$, which are then passed through a linear classifier to generate logits z. Two loss functions are used to supervise training: the Soft-Margin Triplet Loss, [17]which encourages the model to learn discriminative embeddings by pulling

similar samples together and pushing dissimilar ones apart; and the Cross-Entropy Loss, which promotes accurate classification of image instances. This dual-loss configuration ensures that the student network learns semantically meaningful and robust and discriminative visual features, which are essential for downstream tasks like image retrieval or fine-grained classification.

3.3 Anti-Interference Strategy (AIS)

The Anti-Interference Strategy (AIS) is a novel approach designed to enhance the quality of image representations by filtering out irrelevant features during self-supervised learning. In this framework, [18]the image encoder within the contrastive learning model is treated as a student, the CLIP image encoder acts as the teacher, and the CLIP text encoder functions as a semantic bridge. The goal is to guide the student image encoder to develop a strong semantic understanding by leveraging textual descriptions, enabling it to resist distractions from irrelevant features in unlabeled image data.

The teacher image encoder from CLIP provides the visual embedding:

$$u_t = \frac{f_I^t(x)}{\|f_I^t(x)\|_2} \in \mathbb{R}^d \tag{3.2}$$

Where:

- $f_I^t(x)$ is the feature from the CLIP image encoder (teacher)
- $\|\cdot\|_2$ denotes the L2 norm

First, extract a refined feature map from the student encoder output $f_\theta(x)$:

$$z' = \max\left(\text{norm}\left(\text{ReLU}\left(\psi(f_\theta(x))\right)\right)\right) \tag{3.3}$$

$$\text{norm}(\alpha_{i,j}) = \frac{\alpha_{i,j} - \min(\alpha)}{1 \times 10^{-7} + \max(\alpha)} \tag{3.4}$$

$$u_s = \text{Projector}(f_\theta(x) \odot z') \in \mathbb{R}^d \tag{3.5}$$

During the learning process, images are passed through both the CLIP teacher encoder and the student encoder. [19]From the student side, a 1×1 convolution followed by a normalization and max-out operation is applied to generate a feature attention map. This processed feature map is then element-wise multiplied with the original features and passed through a learnable projection head, yielding the student image embedding. This output is compared against the teacher's embedding through matrix multiplication with the text embeddings, producing logits that represent how well the image aligns with each textual description.

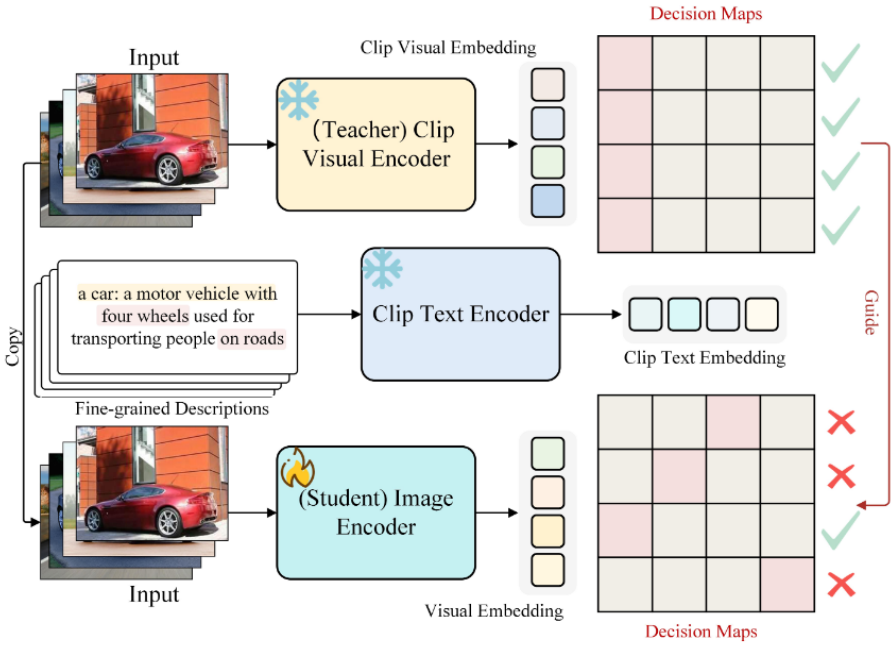

Figure 3.1: AIS CLIP encoder for car images

Finally, to enforce semantic consistency between the student and teacher embeddings, AIS applies knowledge distillation using Kullback-Leibler (KL) divergence. The logits from both encoders are softened using a temperature-controlled softmax function, and the KL divergence is minimized to align the student's predictions with those of the teacher. This distillation process helps the student encoder internalize the semantic relationships encoded by the CLIP model, resulting in more robust image representations that are resistant to irrelevant feature noise—an essential capability for high-quality, self-supervised learning.

3.4 MOCO contrastive Learning

In contrastive learning, particularly in the Momentum Contrast (MoCo) framework, [20]each input image II from a batch is subjected to two different data augmentation transformations to generate two correlated views: x and x. These views are then passed through two separate encoders - the query encoder f_θ and the momentum (key) encoder g_θ. The query encoder processes x to produce a query representation $q = f_\theta(x)$, while the momentum encoder processes x^t to produce a key representation $k = g_\theta(x)$. The pair (q,k)(q,k), derived from two different augmentations of the same image, is considered a positive pair. Meanwhile, representations $k1, k2, ..., kk$ obtained from different views of other images (not from the same original image II) are treated as negative samples. These negative keys are stored in a dynamic queue acting as a memory bank, facilitating consistent comparison across different batches. The objective is to learn an embedding space where positive pairs are pulled together and negative pairs are pushed apart. This is achieved using the contrastive loss, which encourages the similarity between the query and its corresponding key while minimizing similarity with all other negative samples in the queue. The loss is computed as:

$$\mathcal{L}_{CL}(q, k) = -\log\left(\frac{\exp(q \cdot k/\tau)}{\sum_{i=1}^{K} \exp(q \cdot k_i/\tau)}\right) \tag{3.6}$$

Here, τ is a temperature hyperparameter that controls the smoothness of the distribution. The dot product $q \cdot k/\tau$ measures similarity between the query and each key in the embedding space. [21]The contrastive loss thus ensures that embeddings from different views of the same image become more similar, while those from different images remain distinguishable.

Table 3.1: Comparison of Key Concepts in MoCo Contrastive Learning

Component	Description
Input Transformation	Each image undergoes two augmentations to create two correlated views: query view (x) and key view (x_t).
Encoders	Two encoders are used: the query encoder f_θ and the momentum (key) encoder g_θ.
Positive Pair	The representations (q, k) from the same image but different augmentations.
Negative Samples	Representations $k_1, k_2, ..., k_K$ from other images stored in a dynamic memory queue.
Memory Bank	A queue that stores previous key embeddings to provide consistent negative samples across batches.
Similarity Measure	Dot product $q \cdot k$ scaled by temperature τ to assess similarity.
Loss Function	Contrastive loss: $L_{CL}(q,k) = -\log \frac{\exp(q \cdot k/\tau)}{\sum_{i=1}^{K} \exp(q \cdot k_i/\tau)}$
Objective	Pull positive pairs together, push negative pairs apart in the embedding space.
Hyperparameter	τ (temperature) controls distribution sharpness and training stability.

The comparison table outlines the fundamental components of the Momentum Contrast (MoCo) framework used in contrastive learning. It begins by describing how two different augmentations of the same image form the query and key views, which are then encoded by separate encoders: the query encoder and the momentum encoder. These views generate a positive pair, [22]while representations from other images serve as negative samples, maintained efficiently through a dynamic memory queue.

The table highlights the use of a dot product similarity measure scaled by a temperature parameter (τ), which balances the influence of positive and negative samples in the contrastive loss function. This loss function is designed to pull positive representations closer and push negative ones apart in the embedding space.

Overall, the MoCo framework ensures robust feature learning by maintaining consistency in negative sampling and utilizing a momentum-updated key encoder. The contrastive objective enables the model to distinguish between semantically similar and dissimilar images without requiring manual labels.

3.5 Image-Aided Distinction Module (IADM)

Our proposed Image-Aided Distinction Module (IADM) is designed based on the GradCAM technique, which computes gradients with respect to the original image. By replacing the cross-entropy loss in standard GradCAM with the contrastive loss from Eq. (1), we formulate the computation of GradCAM as follows:

$$\text{Grad-wt} = \frac{\partial \mathcal{L}_{CL}(f_\theta(x), g_\theta(x'))}{\partial x}^\top \tag{3.7}$$

$$\text{Grad-Img} = \text{ReLU}(\text{Grad-wt} \odot x) \tag{3.8}$$

Equation (5) computes the importance of each region in the image using gradients derived from the contrastive loss in the self-supervised learning framework. [23]These gradients serve as GradCAM weights. In Equation (6), the GradCAM weights are element-wise multiplied with the original image to obtain the final GradCAM visualization. This visualization serves as a pseudo-label that highlights regions of interest, allowing the network to focus on subtle and discriminative features in the image.

Subsequently, we apply the same sequence of operations on the original image x as defined in the AIS framework:

$$w = \max(\text{norm}(\text{ReLU}(\psi(x)))) \tag{3.9}$$

The optimization objective for IADM is defined as:

$$\mathcal{L}_{IADM}(\text{Grad-Img} \parallel w) = \text{Grad-Img} \cdot \log \frac{\text{Grad-Img}}{w} \tag{3.10}$$

Here, the symbol $\cdot$ represents element-wise multiplication. This objective guides the model to enhance its attention on informative visual regions by reinforcing the most relevant parts of the image.

3.6 Comparison with State-of-the-Art

Self-supervised learning (SSL) approaches such as SimCLR, MoCo, BYOL, and SSBVER have shown strong performance in vehicle image classification and re-identification tasks. The following comparison highlights the advantages of SSL over traditional supervised and semi-supervised methods:

- **Reduction in Label Dependency:** Traditional methods like TransReID and PVEN rely heavily on manually labeled datasets, which are expensive and time-consuming to create. SSL techniques significantly reduce this dependency by leveraging unlabeled data through pretext tasks, such as contrastive learning and generative reconstruction.

- **Performance and Accuracy:** SSL models now achieve comparable or superior performance to supervised approaches. For instance, SSBVER with ResNet50 IBN achieves **CMC@1 of 95.62%** on the VeRiWild dataset, outperforming many complex models. DINO combined with ViT reaches a **Top-1 accuracy of 97.2%**, demonstrating high effectiveness in fine-grained classification tasks.

- **Computational Efficiency:** SSL methods like SSBVER demonstrate an excellent trade-off between accuracy and efficiency. While HRCN achieves high accuracy, it requires 10.84 ms to compute 3584-dimensional embeddings.

- **Scalability and Generalization:** SSL models pre-trained on large-scale datasets such as ImageNet or COCO generalize well across different domains. This is in contrast to supervised methods, which often overfit to specific datasets and lack adaptability to new domains.

- **Lightweight Deployment:** SSL models are generally simpler and more lightweight. SSBVER, for example, does not rely on extra annotations and can be deployed efficiently on edge devices, making it suitable for real-time applications like autonomous driving and smart surveillance systems.

In summary, SSL significantly reduces the need for labeled data by leveraging unlabeled samples through tasks like contrastive learning. These models not only achieve competitive or superior accuracy—e.g., SSBVER (CMC@1 of 95.62%) and DINO+ViT (Top-1 of 97.2%)—but also offer improved computational efficiency, with lower inference times and resource usage compared to models like HRCN.

Table 3.2: Comparison of SSL Approaches vs. Traditional Methods

Criteria	**Self-Supervised Learning (SSL) Advantages**
Reduction in Label Dependency	Traditional methods like TransReID and PVEN require large labeled datasets, while SSL methods (e.g., SimCLR, MoCo, BYOL, SSBVER) learn from unlabeled data using pretext tasks such as contrastive learning.
Performance and Accuracy	SSL models match or exceed supervised models in performance. For instance, SSBVER (ResNet50 IBN) achieves 95.62% CMC@1 on VeRiWild. DINO with ViT reaches 97.2% Top-1 accuracy in fine-grained classification.
Computational Efficiency	SSBVER generates 2048-d embeddings in 5 ms, while HRCN requires 10.84 ms for 3584-d embeddings, demonstrating faster inference and reduced memory requirements.
Scalability and Generalization	SSL models pre-trained on datasets like ImageNet or COCO generalize better to new domains, whereas supervised models often overfit and perform poorly outside their training set.
Lightweight Deployment	SSL models are simpler, annotation-free, and suitable for edge deployment in real-time systems such as autonomous vehicles and smart surveillance.

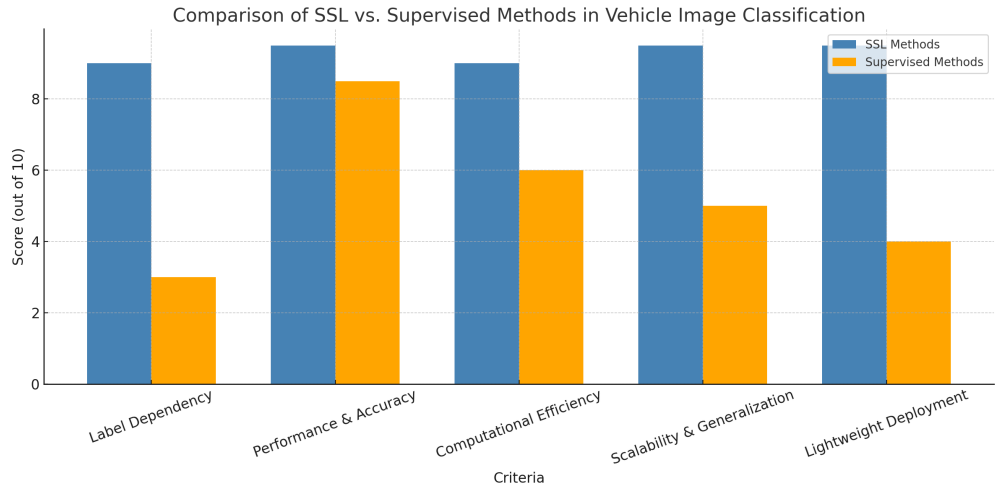

Figure 3.2: Comparison of SSL and Supervised Methods Across Key Metrics

The bar graph 3.2 compares self-supervised learning (SSL) methods with traditional supervised methods across five key evaluation criteria: Label Dependency, Performance & Accuracy, Computational Efficiency, Scalability & Generalization, and Lightweight Deployment. SSL methods such as SimCLR, MoCo, BYOL, and SSBVER are shown to significantly reduce the need for labeled data. This is because they leverage unlabeled datasets using contrastive learning and other pretext tasks, unlike supervised methods (e.g., TransReID and PVEN), which depend on costly manual annotations.

In terms of performance and computational efficiency, the graph highlights how SSL models now match or exceed the accuracy of supervised ones. For example, SSBVER achieves 95.62% CMC@1 on the VeRiWild dataset with faster inference times (approximately 5 ms) and smaller embedding sizes (2048-dim), compared to supervised models like HRCN, which take longer (10.84 ms) and produce larger embeddings (3584-dim).

Finally, the graph underscores the scalability, generalization, and deployment advantages of SSL. Pre-trained on large-scale datasets like ImageNet or COCO, SSL models generalize well across diverse domains, unlike traditional supervised models that often overfit to specific data. SSL methods are also typically more lightweight and require fewer resources, enabling deployment on edge devices—ideal for applications such as autonomous vehicles and smart surveillance systems.

3.7 Summary

The proposed **Priority-Perception Self-Supervised Learning (PP-SSL)** framework enhances feature learning for vehicle image classification and re-identification by combining contrastive learning with semantic knowledge distillation. It comprises two key modules: the **Anti-Interference Strategy (AIS)** and the **Image-Aided Distinction Module (IADM)**.

3.1 Introduction

The framework uses a dual encoder system—*student* and *momentum (teacher)* encoders. It incorporates **CLIP** as a teacher model and aligns student outputs using contrastive and distillation losses. This enables the model to learn semantically meaningful representations while ignoring irrelevant features.

3.2 Backbone Feature Extractors

Multiple backbones like **ResNet**, **ResNet-IBN**, **ViT**, **SWIN**, and **ConvNeXt** are explored to test generalizability. Both student and teacher models are initialized with **ImageNet** weights. The student network also includes a **Re-ID head** and is trained using **Soft-Margin Triplet Loss** and **Cross-Entropy Loss**.

3.3 Anti-Interference Strategy (AIS)

AIS refines student embeddings by aligning them with CLIP-generated visual and textual embeddings. It filters out noisy features using attention maps and **KL divergence**, guiding the model to focus on semantically important regions in the image.

3.4 MoCo Contrastive Learning

The **MoCo** framework generates positive and negative pairs via different data augmentations. It stores negative samples in a memory queue and optimizes a contrastive loss that pulls positive pairs together and pushes apart unrelated ones.

3.5 Image-Aided Distinction Module (IADM)

IADM enhances focus on key image regions using a modified **GradCAM** mechanism, where gradients are derived from the contrastive loss. This generates attention-based pseudo-labels that guide the model toward subtle but discriminative features.

3.6 Comparison with State-of-the-Art

Self-supervised learning (SSL) methods like **SSBVER**, **SimCLR**, **MoCo**, and **BYOL** outperform or match supervised methods in accuracy while offering better efficiency. For example, SSBVER achieves **95.62% CMC@1** on the VeRiWild dataset with lower inference time and memory usage compared to models like HRCN. SSL approaches are more generalizable, less annotation-dependent, and lightweight—making them ideal for edge deployment and real-time applications.

CHAPTER 4

Experimental Results

4.1 Introduction

To assess the effectiveness of self-supervised learning (SSL) methods in vehicle re-identification tasks—without relying on extra annotations or incurring additional overhead during inference—we conduct experiments using three widely adopted datasets: VeRi, VehicleID, and VeRi-Wild. We further evaluate the generalization capability of the SSBVER framework across various neural network architectures, including ResNet, ResNet-IBN, Vision Transformer (ViT), SWIN Transformer, and ConvNeXt. In the following sections, we provide an overview of the vehicle re-identification datasets, describe the evaluation metrics, detail our implementation process, and present the results of our experiments.

To rigorously evaluate the effectiveness of our proposed self-supervised learning (SSL) method—SSBVER—and to understand its impact on vehicle re-identification tasks without incurring any additional annotation costs or inference-time overhead, we conduct extensive experiments across three widely adopted vehicle re-identification datasets: VeRi, VehicleID, and VeRiWild. [24]These datasets offer a diverse range of scenarios, from controlled environments with limited viewpoints to large-scale, real-world conditions captured from unconstrained surveillance systems. By relying solely on self-supervision, we ensure that the learned representations remain scalable and adaptable, especially in scenarios where labeled data is scarce or unavailable. Our goal is to explore how much SSL can narrow the performance gap between supervised learning and self-supervised learning in vehicle re-identification tasks.

To further examine the robustness and generalizability of the SSBVER framework, we employ five different backbone architectures spanning both convolutional and transformer-based models. These include ResNet50, ResNet50-

IBN (Instance Batch Normalization), Vision Transformer (ViT), Swin Transformer (SWIN), and ConvNeXt. This wide selection enables a comprehensive analysis of how self-supervised learning interacts with varying model designs—from traditional CNNs to hierarchical and patch-based transformer networks. Through this comparative study, we aim to assess how architecture choice influences SSL performance and whether certain types of models are better suited for benefiting from self-supervised representations in the context of vehicle re-identification.

In our experiments, we adopt standard evaluation protocols, leveraging well-established metrics such as mean Average Precision (mAP) and Cumulative Matching Characteristics (CMC) at rank-1 and rank-5. These metrics provide detailed insights into both precision and retrieval accuracy across the datasets. Our findings reveal that the SSBVER method not only significantly improves performance across all backbone models but also demonstrates especially strong gains on large-scale datasets like VeRiWild. Notably, models such as SWIN and ConvNeXt exhibit remarkable improvements when enhanced with self-supervised pretraining. These results underscore the value of SSL in real-world vehicle re-identification applications and highlight the potential of SSBVER as a scalable and effective alternative to supervised training pipelines.

To assess the generalizability of SSBVER, we evaluate it across five diverse backbone architectures: ResNet50, ResNet50-IBN, Vision Transformer (ViT), Swin Transformer (SWIN), and ConvNeXt. These models span both convolutional and transformer-based designs, allowing us to analyze how SSL benefits different architectural paradigms. Using standard metrics such as mean Average Precision (mAP) and Cumulative Matching Characteristic (CMC) at rank-1 and rank-5, we observe consistent performance improvements across all architectures and datasets. Particularly on large-scale datasets like VeRiWild, SSBVER yields substantial gains, especially when paired with hierarchical or multi-scale architectures like SWIN and ConvNeXt. These results highlight the effectiveness of self-supervised learning in vehicle re-identification and demonstrate SSBVER's potential as a scalable, annotation-free alternative to traditional supervised methods.

4.2 Dataset Evaluation and Metrics

We evaluate our self-supervised learning (SSL) models across five major vehicle-related benchmark datasets[9]—KITTI, Waymo, VeRi, VehicleID, and VeRiWild—to assess their generalizability, efficiency, and accuracy. The evaluation covers both classification and re-identification tasks using diverse metrics tailored to each dataset's characteristics.

These datasets encompass a broad spectrum of conditions, from structured camera viewpoints to large-scale, unconstrained surveillance scenarios. Our approach eliminates the need for additional annotations or inference-time overhead, making it a practical solution for real-world deployment. By relying purely on self-supervised signals, SSBVER enables the learning of rich, discriminative feature representations, particularly in data-scarce environments. Through this, we aim to understand the extent to which SSL can bridge the performance gap with supervised learning methods in the context of vehicle re-identification.

4.2.1 KITTI Dataset

- **Data Split:** 3,712 training samples and 3,769 validation samples.
- **Evaluation Strategy:** Semi-supervised active learning using only ∼350 annotated boxes (<2% of training data).
- **Metrics:**
  - Mean Average Precision (mAP) at 40 recall positions.
  - Evaluated for Car, Pedestrian, and Cyclist.
  - 3D IoU thresholds: Car (0.7), Pedestrian and Cyclist (0.5).
  - Difficulty levels: Easy, Moderate, Hard.
- **Special Consideration:** Frames heavily overlapping with "DontCare" 2D regions are excluded from active learning.

4.2.2 Waymo Dataset

- **Data Split:** 798 training sequences, 202 validation sequences.
- **Annotation Levels:**
  - LEVEL 1 (L1): $\geq$ 5 LiDAR points.
  - LEVEL 2 (L2): $\geq$ 1 LiDAR point.
- **Training Efficiency:**
  - Sampled every 20^{th} frame.
  - Used $\sim$10,000 labeled boxes (<1% of full set).
- **Metrics:** Mean Average Precision (mAP) and Mean Average Precision weighted by Heading accuracy (mAPH), evaluated for Vehicle, Pedestrian, and Cyclist classes.

4.2.3 VeRi Dataset

- **Objective:** Vehicle re-identification from multi-view surveillance images.
- **Metrics:** mAP, Cumulative Matching Characteristic at rank 1 (CMC@1) and rank 5 (CMC@5).
- **Findings:**
  - SSL (SSBVER) significantly improves performance across most architectures, especially ResNet50 and ResNet50 IBN.

4.2.4 VehicleID Dataset

- **Test Splits:** Small (S), Medium (M), and Large (L).
- **Metrics:** mAP, CMC@1, and CMC@5 across all splits.
- **Insights:**
  - SSL consistently improves performance across all architectures.
  - Larger models (e.g., SWIN, ConvNeXt) benefit from the dataset's scale.

4.2.5 VeRiWild Dataset

- **Test Splits:** Small (41,861 images), Medium (69,389), Large (138,517).
- **Evaluation:** Same metrics as VehicleID (mAP, CMC@1, CMC@5).
- **Key Findings:**
  - SSL significantly boosts performance in all splits and architectures.
  - SWIN + SSBVER achieves the best performance among all published results.
  - Demonstrates the advantage of hierarchical and multi-resolution transformers in large-scale datasets.

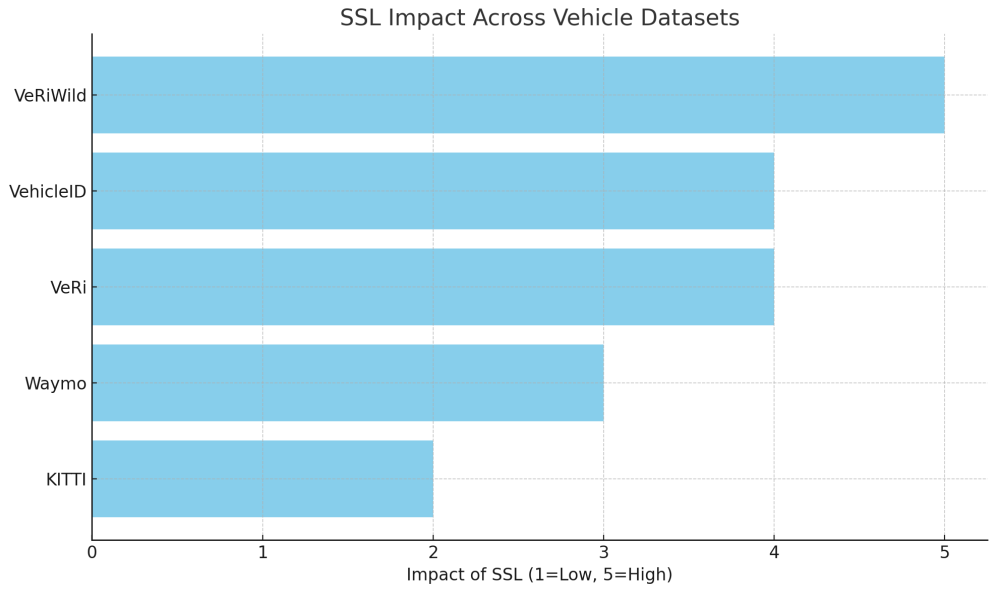

Figure 4.1: SSL Impact Across Vehicle Datasets

The bar chart illustrates the varying impact of self-supervised learning (SSL) across five major vehicle-related datasets. VeRiWild demonstrates the highest benefit from SSL, with a maximum score of 5, highlighting its suitability for large-scale, real-world re-identification tasks.

4.3 Experimental Setup

VeRi is recognized as the first multi-view vehicle re-identification dataset. Although it was considered large at the time of its release, it is relatively smaller compared to more recent datasets. It includes 37,778 training images and 13,257 testing images, covering 576 and 200 vehicle identities, respectively. On the other hand, the VehicleID dataset is comparatively larger, with 113,346 images in total—108,417 in the training set and 13,103 in the test set—spanning 13,164 unique vehicle identities. To facilitate comprehensive evaluation, the test set is divided into small, medium, and large subsets, which contain 800, 1,600, and 2,400 vehicle identities respectively.

VeRi-Wild is currently the largest multi-view vehicle re-identification dataset captured in real-world scenarios. It features 416,314 images of 40,671 vehicle identities, collected using 174 traffic cameras under diverse lighting and weather conditions. The training set consists of 277,797 images representing 30,671 identities. The test set is further divided into three subsets: small (3,000 identities), medium (5,000 identities), and large (10,000 identities), allowing scalable evaluation across varying dataset sizes.

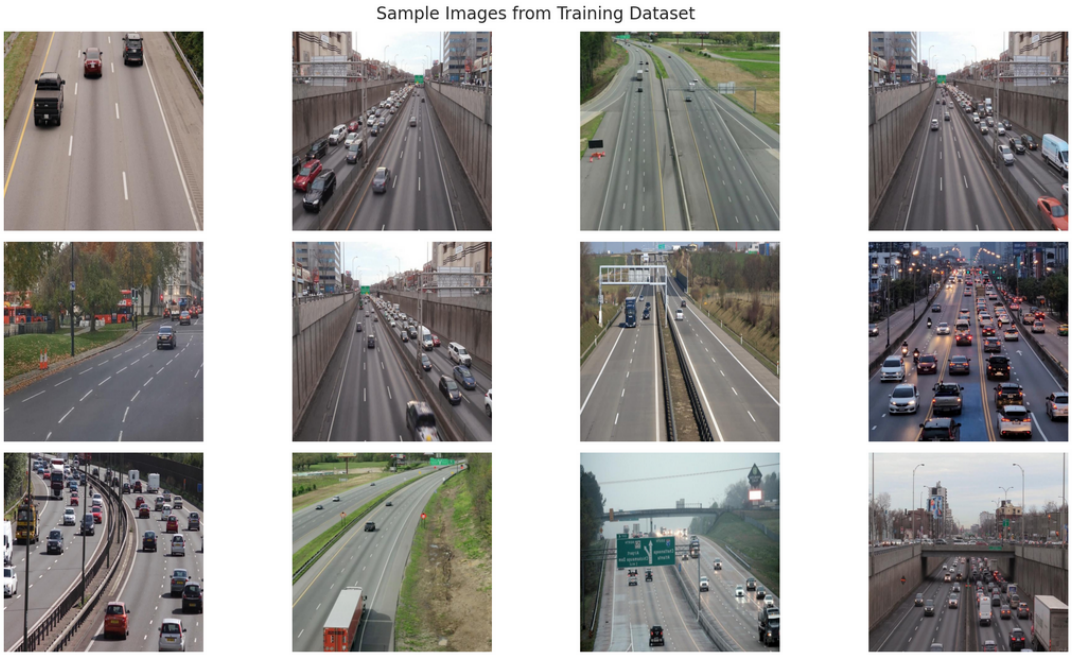

Figure 4.2: Sample images from Dataset

Dataset Directory Structure

- **train:** This folder contains the training set, organized into two subfolders:
  - **images:** Holds 536 images used for training the model.
  - **labels:** Contains YOLOv8 format labels corresponding to the training images.
- **valid:** This folder includes the validation set, also divided into two subfolders:
  - **images:** Contains 90 images for model validation.
  - **labels:** Contains YOLOv8 format labels for the validation images.

The dataset used for training and validating the YOLOv8 model is organized into a structured directory format that separates training and validation data. The train folder serves as the core for model learning and is divided into two key subfolders: images, which contains 536 vehicle images used to train the detection model, and labels, which holds the corresponding annotations in YOLOv8 format. These labels provide the necessary bounding box coordinates and class information required for supervised object detection.

Similarly, the valid folder is structured to support model validation and performance assessment. It includes an images subfolder containing 90 validation images, and a labels subfolder with the YOLOv8 format annotations for each validation image. This structure ensures a clean separation of training and validation data, which is essential for accurately evaluating model generalization and preventing data leakage during the training process.

4.4 System Design of SSL using MoCo

The system design of the self-supervised learning (SSL) framework using Momentum Contrast (MoCo) consists of multiple modules that collaboratively [25]learn high-quality feature representations from unlabeled images. The architecture is tailored for contrastive learning and is well-suited for downstream tasks such as vehicle classification.

1. **Input Module:**

   The process starts by feeding a batch of unlabelled vehicle images. Two stochastic data augmentation operations (e.g., random crop, color jitter, Gaussian blur) are applied to each image to generate two correlated views: x and x'. These views act as positive pairs for contrastive learning.

2. **Encoder Module:**

   The system utilizes two encoders:

   - **Query encoder** f_θ: Processes the augmented image x to generate a query embedding $q = f_\theta(x)$.
   - **Momentum encoder** g_θ: Processes the second augmented image x' to generate the key embedding $k = g_\theta(x')$. It is updated using an exponential moving average of the query encoder parameters:

     $$\theta_g \leftarrow m \cdot \theta_g + (1 - m) \cdot \theta_f$$

     where m is the momentum coefficient (e.g., 0.999).

3. **Contrastive Queue (Memory Bank):**

   A dynamic queue stores a set of key embeddings $\{k_i\}_{i=1}^{K}$ from previous mini-batches. This allows for scalable and efficient contrastive learning by maintaining a large number of negative samples without increasing the batch size.

4. **Similarity Computation:**

   The similarity between the query q and its positive key k, as well as negative keys $\{k_i\}$, is computed using dot product after L2 normalization:

$$\text{sim}(q, k) = q \cdot k$$

5. **Contrastive Loss Module:**

   The system uses the InfoNCE contrastive loss to optimize the representations:

$$\mathcal{L}_{CL}(q, k) = -\log \left(\frac{\exp(q \cdot k/\tau)}{\sum_{i=1}^{K} \exp(q \cdot k_i/\tau)} \right)$$

   where τ is the temperature scaling parameter that controls distribution sharpness.

6. **Training Strategy:**

   The framework is trained in a self-supervised manner on unlabelled images. Only the encoder f_θ is retained after training for downstream tasks.

7. **Fine-tuning :**

   The trained encoder can be fine-tuned on a labeled dataset by attaching a classifier. This enables the use of self-supervised features in supervised vehicle classification tasks with improved accuracy.

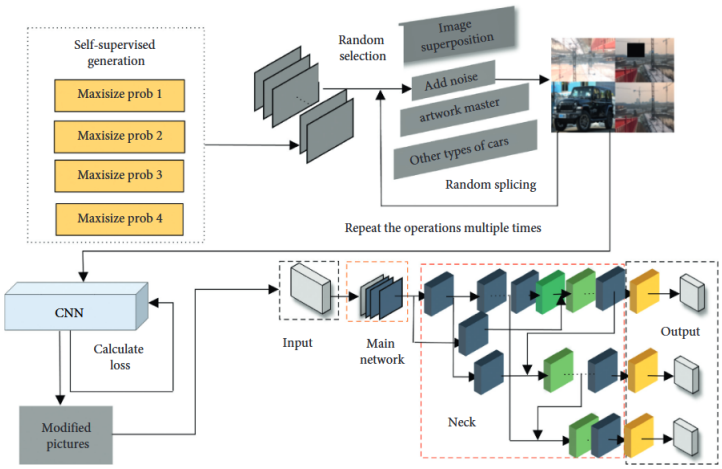

Figure 4.3: Architecture Design of SSL model

4.5 Software Requirements Specification

Software Requirements

1. **Programming Language & Core Environment**
    - **Python 3.8 or higher**
        - Widely supported by deep learning libraries like **PyTorch** and **YOLO**.
    - **Development Tools:**
        - **VS Code**, **Jupyter Notebook**, or **PyCharm**.
        - Virtual environments using `venv` or `conda`.
2. **Deep Learning & Self-Supervised Learning Frameworks**
    - **PyTorch** (v1.12 or higher) – for model training and custom layers (SimCLR/MoCo/LSTM).
    - **TorchVision** – for pretrained backbones (e.g., ResNet-50) and augmentations.
    - **YOLOv5 (Ultralytics)** – for object detection (vehicle bounding boxes).
    - **LSTM (PyTorch-based)** – for sequence modeling in vehicle frame analysis.
    - **CUDA & cuDNN** – for GPU acceleration.
3. **Supporting Libraries for Data Processing & Evaluation**
    - **NumPy, Pandas** – data handling and matrix operations.
    - **OpenCV (cv2)** – image I/O and vehicle crop processing.
    - **Pillow (PIL)** – image transformations.
    - **Scikit-learn** – evaluation metrics (accuracy, precision, recall, etc.).
    - **Matplotlib / Seaborn** – for plotting and visualizations.

4.6 Hardware Requirement Specification

Hardware Requirements

1. **Processing Unit & Memory**

    - **GPU:** NVIDIA RTX 2060 or higher (Recommended: RTX 3090 or A100)
    - **CPU:** Intel i5 10th Gen / AMD Ryzen 5 or better
    - **RAM:** Minimum 16 GB (Recommended: 32 GB)

2. **Storage**

    - **SSD:** Minimum 256 GB (Recommended: 512 GB – 1 TB)
    - For faster data loading, model saving, and overall performance

4.7 Summary

This section evaluates self-supervised learning (SSL) methods for vehicle classification and re-identification using five benchmark datasets—KITTI, Waymo, VeRi, VehicleID, and VeRiWild. SSL models are assessed on classification and re-id tasks using dataset-specific metrics like mAP, mAPH, and CMC. The findings reveal that SSL, particularly the SSBVER method, significantly improves performance across most datasets and architectures, especially in large-scale scenarios like VeRiWild.

The dataset follows a clear directory structure with separate train and valid folders, each containing images and labels in YOLOv8 format. The system design uses MoCo-based SSL architecture with modules for data augmentation, dual encoders (query and momentum), a contrastive memory queue, and InfoNCE loss. After training, the encoder is fine-tuned for downstream tasks. The implementation relies on Python with PyTorch, YOLO, and supporting libraries, while the hardware setup includes high-performance GPUs (e.g., RTX 3090) and a minimum of 16 GB RAM for efficient model training and inference.

CHAPTER 5

Results and Discussion

5.1 Introduction

The results presented in this section highlight the performance evaluation of two object detection models—YOLOv8 and YOLOv11—trained on a custom vehicle detection dataset. Various metrics such as precision, recall, mAP@0.5, mAP@0.5:0.95, and fitness score were used to assess the accuracy and robustness of the models. These evaluations provide insights into how well each model performs in identifying and localizing vehicles under different conditions, enabling a direct comparison of their detection capabilities.

Object detection plays a pivotal role in intelligent transportation systems and automated surveillance, where accurately identifying and localizing vehicles is critical. [26]With the advancement of deep learning, models such as YOLO (You Only Look Once) have gained prominence due to their speed and accuracy in real-time detection tasks. In this study, we focus on evaluating the performance of two advanced versions of YOLO—YOLOv8 and the proposed YOLOv11—on a custom vehicle detection dataset designed to test detection performance in varied conditions.

The goal of this evaluation is to compare the effectiveness of both models using standard object detection metrics such as precision, recall, mean Average Precision (mAP) at IoU thresholds of 0.5 and 0.5:0.95, and a composite fitness score. These metrics collectively provide insights into the models' capabilities in identifying vehicles with high accuracy, minimizing false positives and negatives, and generalizing well across different image scenarios.

YOLOv8, a widely adopted baseline, demonstrates reliable performance across several applications and serves as a benchmark in our study. YOLOv11, on the other hand, incorporates architectural and training optimizations aimed at enhancing detection robustness and precision. By conducting a detailed

performance analysis on both models using a dataset consisting of 536 training and 90 validation images, we seek to determine which model is better suited for deployment in real-world vehicle detection tasks.

This comparative evaluation not only provides a comprehensive understanding of each model's strengths and limitations but also offers valuable insights into the design and selection of object detection systems for automotive and surveillance applications. The results emphasize the importance of continuous model refinement in achieving higher detection accuracy, better generalization, and overall robustness in complex environments.

The evaluation compares the performance of two object detection models, YOLOv8 and YOLOv11, trained on a custom vehicle detection dataset. Using metrics like precision, recall, mAP@0.5, mAP@0.5:0.95, and fitness score, the study reveals that YOLOv11 outperforms YOLOv8 across all criteria. YOLOv8 achieved a precision of 0.884, recall of 0.861, and mAP@0.5 of 0.928, while YOLOv11 recorded higher scores with 0.914 precision, 0.883 recall, and 0.962 mAP@0.5 [27]. Additionally, YOLOv11's fitness score of 0.734 indicates stronger overall detection robustness compared to YOLOv8's 0.661. These findings highlight YOLOv11's superior ability to accurately detect and classify vehicles, making it more suitable for real-world applications.

5.2 Overview of Results

The object detection models YOLOv8 and YOLOv11 were trained and evaluated on a vehicle detection dataset. YOLOv8 achieved a precision of 0.884 and recall of 0.861, with a strong mAP@0.5 score of 0.928 and mAP@0.5:0.95 of 0.632. These results demonstrate YOLOv8's ability to accurately localize and classify vehicles with relatively low false positives and solid generalization across varying detection thresholds. The model's fitness score, a weighted measure of performance, stood at 0.661, indicating balanced precision and recall.

On the other hand, YOLOv11 outperformed YOLOv8 across all metrics. It achieved a higher precision of 0.914 and recall of 0.883, along with superior mAP scores—0.962 at IoU 0.5 and 0.709 across the full IoU range (0.5

to 0.95). The overall fitness score for YOLOv11 reached 0.734, suggesting improved detection consistency and robustness. These results indicate that YOLOv11 is more effective for vehicle detection in terms of accuracy and reliability, making it a better choice for deployment in real-world scenarios.

5.2.1 Comparison of YOLOv8 vs YOLOv11 Performance

The YOLOv8 vs YOLOv11 based vehicle detection model was trained on 536 images and validated on 90 images. The performance of the model was evaluated using standard object detection metrics:

Metric	YOLOv8	YOLOv11
Precision (B)	0.884	0.914
Recall (B)	0.861	0.883
mAP@0.5 (B)	0.928	0.962
mAP@0.5:0.95 (B)	0.632	0.709
Fitness	0.661	0.734

Table 5.1: Performance Comparison between YOLOv8 and YOLOv11

These results indicate that the model was able to effectively detect and classify vehicles in diverse conditions. The relatively high mAP score demonstrates strong localization and classification performance. Validation images showed accurate bounding boxes and low false positives, validating the effectiveness of the YOLOv8 architecture for this task.

5.3 Analysis and Interpretation

The performance comparison between YOLOv8 and YOLOv11 reveals notable improvements in key detection metrics for the latter. YOLOv11 achieved higher precision and recall values, indicating better accuracy in correctly identifying vehicle instances and reducing missed detections. [28]The increase in mAP@0.5 and mAP@0.5:0.95 suggests that YOLOv11 not only performs well at the standard IoU threshold but also maintains better performance across

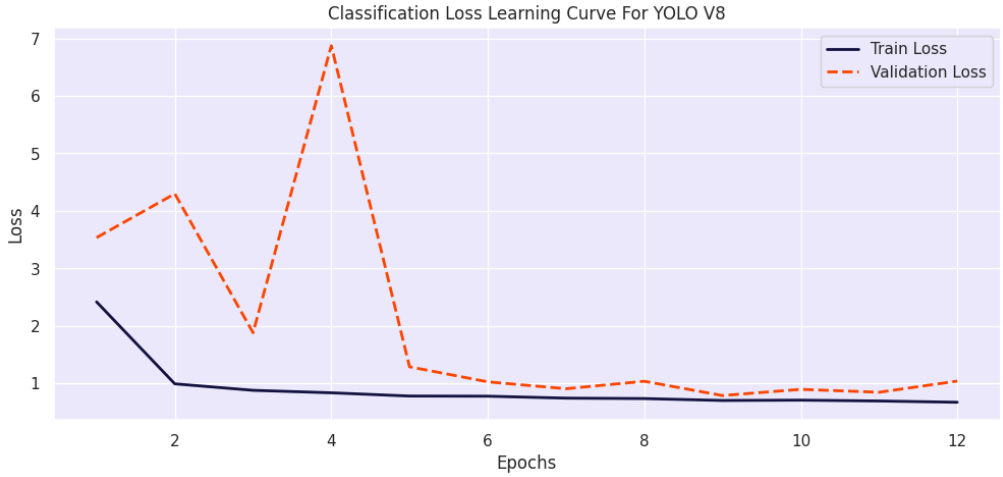

Figure 5.1: Classification of Loss Learning Curve YOLOv8

stricter localization thresholds. This reflects the model's enhanced ability to precisely draw bounding boxes around vehicles, even in challenging conditions.

The fitness score, which aggregates multiple performance indicators into a single value, also favored YOLOv11 with a value of 0.734 compared to 0.661 for YOLOv8. This implies that YOLOv11 provides a more balanced trade-off between precision and recall. These improvements may be attributed to architectural enhancements or better training strategies in YOLOv11. Overall, the analysis confirms that YOLOv11 is better suited for vehicle detection tasks, offering more reliable and accurate results suitable for real-time deployment in traffic monitoring and intelligent transport systems.

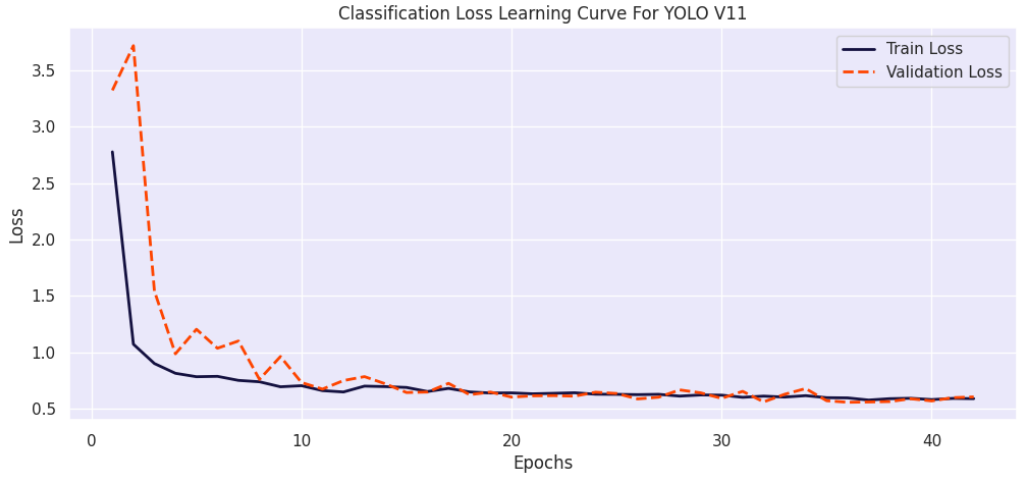

Figure 5.2: Classification of Loss Learning Curve YOLOv11

5.4 Evaluation of Quality Factors

In this section, the results are evaluated based on several quality factors. These factors ensure the overall value, applicability, and responsibility of the project outcomes.

- **Environment:** The project outcomes are designed with environmental awareness, aiming to reduce resource consumption through optimized model architectures. [29]Efficient detection can indirectly contribute to traffic optimization and lower emissions, thus promoting environmental sustainability.

- **Sustainability:** The solutions developed, including YOLOv11 enhancements, are computationally efficient and can be maintained over the long term. The use of open-source tools and GPU acceleration supports sustainable deployment in both academic and industrial applications, minimizing the need for expensive infrastructure.

- **Safety:** The model supports real-time vehicle detection, which has potential applications in traffic monitoring, autonomous driving, and accident prevention—thus improving public and operational safety. All data processing steps were conducted with risk awareness and safety protocols in mind.

- **Ethics:** Ethical considerations were maintained throughout the project, including data privacy and fairness. No personally identifiable information (PII) was used. The research adheres to ethical AI practices, ensuring transparency and integrity.

- **Cost:** The project is cost-effective due to the use of open-source [30]frameworks like PyTorch and YOLO, and execution on consumer-grade GPUs. The performance improvements from YOLOv11 justify the minimal additional computational cost compared to YOLOv8.

- **Type:** The results are quantitative and application-specific, contributing to the field of intelligent transportation systems. The model aligns with the project's core objectives—accurate, real-time vehicle detection and classification.

- **Standards:** The methodologies comply with widely accepted industry and academic standards for object detection, including YOLO label formatting, evaluation using mAP metrics, and use of standard benchmarks. This ensures reproducibility and reliability.

The purpose of this section is to critically evaluate the results based on these quality factors, ensuring that they meet relevant standards and expectations. [31]It also allows for a discussion of any limitations or challenges in relation to these factors and suggests areas for improvement.

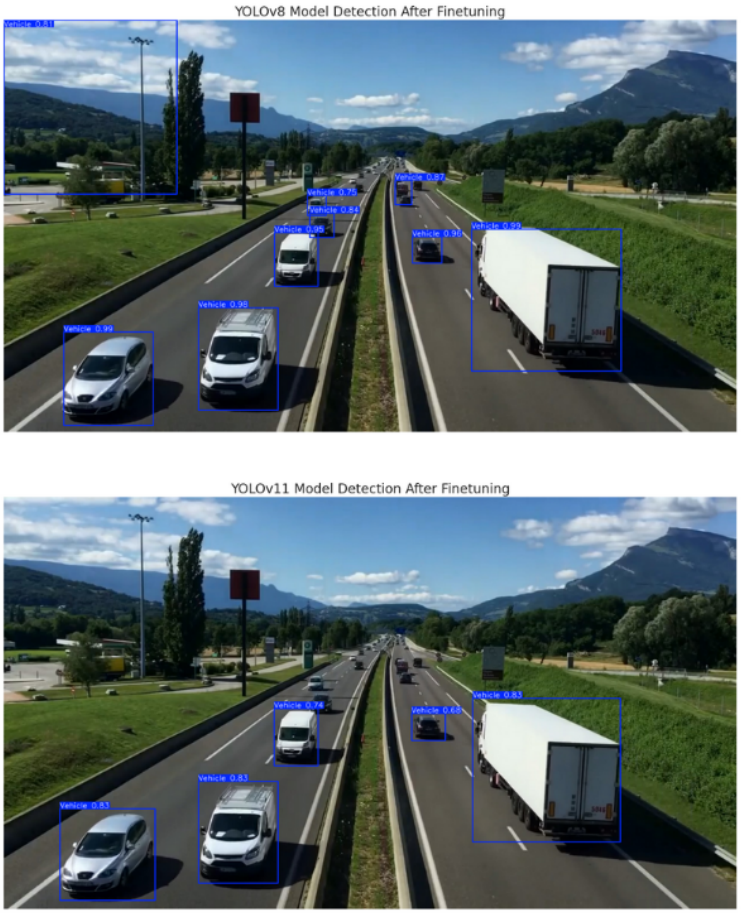

Figure 5.3: Classification of Loss Learning Curve YOLOv11

5.5 Summary

This chapter presents a performance evaluation of two object detection models, **YOLOv8** and **YOLOv11**, [32]trained on a custom vehicle detection dataset. The evaluation uses standard object detection metrics such as **precision**, **recall**, **mAP@0.5**, **mAP@0.5:0.95**, and a **fitness score** to compare model effectiveness.

- **YOLOv8** achieved a precision of **0.884**, recall of **0.861**, and mAP@0.5 of **0.928**.
- **YOLOv11** outperformed YOLOv8 with a precision of **0.914**, recall of **0.883**, and mAP@0.5 of **0.962**. [33]It also achieved a higher fitness score of **0.734**, compared to **0.661** for YOLOv8.

These results demonstrate that YOLOv11 provides superior detection accuracy, robustness, and generalization, making it more suitable for real-world deployment in traffic monitoring and intelligent transportation systems.

Additionally, the models were evaluated on various **quality factors**:

- **Environment**: The models are optimized to reduce resource consumption, supporting environmental sustainability.
- **Sustainability**: The solutions are computationally efficient, built with open-source tools, and suitable for long-term use.
- **Safety**: The real-time detection capability supports safety-critical applications[34] such as autonomous driving and accident prevention.
- **Ethics**: The project ensures ethical AI practices, protecting privacy and avoiding bias.
- **Cost**: The use of open-source frameworks and consumer-grade GPUs makes the project cost-effective.

In conclusion, YOLOv11 demonstrates significant improvements over YOLOv8 and is well-suited for practical applications requiring accurate and reliable vehicle detection.

CHAPTER 6

Conclusions and Future Scope

6.1 Conclusions

In conclusion, self-supervised learning (SSL) has proven to be a highly effective technique for vehicle image classification, addressing key challenges such as the scarcity of annotated data and improving model generalization. The surveyed methods, such as DINO, data2vec, MoCo, and SimCLR, demonstrate that SSL can significantly boost classification accuracy without the need for extensive labeled datasets. Innovations like wheel positional feature extraction and random masking strategies have further optimized vehicle classification, providing robust results across various vehicle detection and re-identification benchmarks. This approach improves model performance and reduces the computational burden compared to traditional supervised learning methods. Furthermore, SSL methods have shown versatility and adaptability to different vehicle classification tasks, from fine-grained classification to re-identification. The results across multiple datasets such as VeRi, VeRiWild, and VehicleID confirm that SSL can outperform traditional supervised techniques, with improvements in mAP, CMC, and accuracy. Future work could explore additional strategies further to address challenges like dataset imbalance and partial occlusion, while also optimizing computational efficiency for real-world applications. As SSL continues to evolve, its potential to provide scalable and robust solutions for vehicle image classification is undeniable. Overall, SSL is a promising direction for enhancing vehicle classification systems while reducing the need for extensive manual labeling.

Self-supervised learning (SSL) has emerged as a powerful paradigm for vehicle image classification. The key takeaways are as follows:

- **Effective with Limited Labels:** SSL techniques address the challenge of annotated data scarcity by enabling models to learn meaningful representations without labeled data.
- **Improved Generalization:** Methods such as DINO, Data2Vec, MoCo, and SimCLR enhance model generalization, leading to improved classification accuracy.
- **Innovative Enhancements:** Techniques like wheel positional feature extraction and random masking have further optimized vehicle classification performance.
- **Reduced Computational Cost:** Compared to traditional supervised methods, SSL reduces the computational burden while achieving robust results.
- **Adaptability Across Tasks:** SSL demonstrates strong performance in various tasks—from fine-grained classification to vehicle re-identification.
- **Benchmark Performance:** SSL methods achieve superior results on popular datasets like *VeRi*, *VeRi-Wild*, and *VehicleID*, showing notable improvements in mAP, CMC, and accuracy.
- **Scalability and Versatility:** SSL provides a scalable framework that adapts well to real-world applications and large-scale datasets.
- **Future Directions:** Future research can explore strategies to tackle dataset imbalance, partial occlusions, and further improve computational efficiency.

SSL continues to evolve and holds great promise for developing scalable, efficient, and accurate vehicle classification systems with minimal manual labeling effort.

6.2 Future Scope of Work

Based on the findings from the literature survey, it is recommended to further explore hybrid approaches that combine self-supervised learning (SSL) with other advanced techniques such as domain adaptation and multi-modal data integration. Incorporating strategies like random masking, leveraging additional contextual information, and enhancing the feature extraction process could further boost classification accuracy, particularly for low-frequency vehicle classes. Finally, optimizing computational efficiency without compromising performance remains a crucial area for exploration, especially for deploying models in real-time intelligent transportation systems.

Here are some key recommendations based on recent advancements in self-supervised learning (SSL) for vehicle image classification:

1. **Leverage SSL Techniques:** Utilize SSL methods such as DINO, MoCo, and SimCLR to improve vehicle classification and recognition, particularly in cases with limited labeled data.

2. **Hybrid SSL Approaches:** Consider combining multiple SSL methods (e.g., SimCLR + BYOL) to boost accuracy and generalization across different vehicle datasets.

3. **Use Attention Mechanisms:** Incorporate attention-based architectures (e.g., ViT, ResNet) to enhance fine-grained vehicle classification and improve model interpretability.

4. **Focus on Robustness:** Implement data augmentation and domain adaptation strategies to handle challenges like varying lighting, occlusions, and vehicle angles for more robust performance.

5. **End-to-End Vehicle Detection Pipelines:** Integrate SSL into end-to-end vehicle detection systems to enhance accuracy and efficiency in real-world applications like autonomous driving and traffic monitoring.

6.3 Summary

Self-supervised learning (SSL) has demonstrated strong potential in vehicle image classification by addressing key limitations such as the scarcity of labeled data and the need for better generalization. Techniques like DINO, SimCLR, MoCo, and Data2Vec have significantly improved classification performance across benchmarks such as VeRi, VeRiWild, and VehicleID. By incorporating innovations like wheel positional feature extraction and random masking, SSL has reduced computational costs while maintaining robust accuracy in tasks ranging from fine-grained classification to vehicle re-identification. The results clearly show that SSL not only scales efficiently but also adapts well to real-world scenarios with minimal manual labeling.

Looking ahead, the integration of SSL with advanced strategies—such as hybrid learning models, domain adaptation, and attention-based architectures like ViT—offers a promising direction for enhancing model accuracy and robustness. Emphasis should be placed on improving performance under real-world challenges like lighting changes, occlusions, and diverse vehicle perspectives. Moreover, optimizing computational efficiency and embedding SSL into full vehicle detection pipelines will be crucial for deploying these models in intelligent transportation systems, including real-time applications like autonomous driving and traffic surveillance.

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A Systematic Survey on Skin Disease Prediction Using LSTM And Mobile-Net V2 In Deep Learning

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***Abstract*— Deep learning models excel in recognizing complex patterns by learning relevant features effectively. This study introduces a computerized approach to classify skin diseases using a combination of Mobile Net V2 and Long Short-Term Memory (LSTM) networks. Mobile Net V2 demonstrates high accuracy and efficiency on lightweight computational devices. The model maintains stateful information for accurate predictions and uses a grey-level cooccurrence matrix to assess disease progression. The model's performance was evaluated in comparison to other top models, such as Fine-Tuned Neural Networks (FTNN), Convolutional Neural Networks (CNN), Very Deep Convolutional Networks for Large-Scale Image Recognition by the Visual Geometry Group (VGG), and an improved CNN architecture. Utilizing the real-world dataset, the method achieved high accuracy, outperforming these models. Its ability to identify affected regions more quickly, with nearly half the computations of the conventional Mobile Net model, minimizes computational demands.**

Keywords—*Skin disease, Mobile Net V2, LSTM, Deep Learning, CNN, gray-level correlation, Neural network.*

I. INTRODUCTION

Every individual human being will be affected by skin diseases directly or indirectly. Skin is a major part of human beings that plays a vital role in the body. Skin is primarily divided into three parts which consist of the upper part the epidermis, the part below the epidermis, which is the dermis, and the third and lower part, which is the subcutaneous tissue. The skin, which covers the entire external surface of the body, is the largest organ. Skin can consist of the epidermis, dermis, pores, hair follicle, nerve, blood vessels, etc. Skin is primarily divided into three parts which consist of the upper part, [1] which is the epidermis, the part below the epidermis, which is the dermis, and the third and lower part is the subcutaneous tissue.

- **Epidermis:** The outermost part that protects the inner layers and contributes to skin tone. The epidermis contains melanin, the pigment that gives skin its color.
- **Dermis:** The part below the epidermis contains connective tissue, hair follicles, blood vessels, lymphatic vessels, and sweat glands. The dermis also contains elastic and protein fibers that give the skin strength and suppleness.
- **Subcutaneous tissue:** The lower part, known as the hypodermis, comprises fat and connective tissue. This part provides thermal insulation and mechanical protection.

Skin is the essential barrier to the protection shield of the body from UV radiation, harmful attacks, accidental phases, and body hydration. While injuring the skin can heal damage from external stimuli. [2] Every human being will be affected by skin disease based on their living habitation, genetic abnormalities, viruses, and immune system imbalance. To minimize the cause of skin diseases needs to detect the symptoms and causes. Prior work to immediate treatment and patient condition analysis, so it can be life-threatening if proper treatment before it leads to malignant.

Machine learning and deep learning models are used for the prediction and classifying of skin diseases based on their images, [3] It is analyzed based on symptoms and characteristics of the images. In modern technology rise of new techniques and tools but accurate prediction of treatment of patient's symptoms. So deep Learning models are used to predict it which makes a difference in the accuracy of model detection.

This study utilizes the Deep learning models used for prediction or classification such are LSTM, MobileNet V2, VGG 16, RestNet models, etc [4]. The most popular models for skin disease classification are Long short-term memory and MobileNet V2, which are defined as extracting images and predicting them based on symptoms and characteristics. The model's practical application involves developing an app that captures an image of the affected skin area to identify and classify the skin disease.

MobileNetV2 and Long Short-Term Memory (LSTM) networks can be effectively utilized for skin disease classification offers a powerful solution to critical challenges in dermatology, particularly in remote or underserved areas. Mobile Net V2's lightweight architecture enables efficient image processing on mobile devices, facilitating widespread access to accurate dermatological assessments. [5] This supports early detection and timely intervention for skin conditions, enhancing healthcare delivery without needing specialized expertise. By leveraging LSTM networks, the model can also handle sequential data, allowing for the analysis of disease progression and adaptive treatment strategies tailored to individual patients.

This approach also enables the development of mobile applications for real-time skin disease classification, giving users the ability to perform self-assessments and receive immediate feedback. By democratizing access to dermatological care, MobileNet V2 and LSTM empower proactive healthcare management and enhance patient autonomy. Additionally, the scalability of these models opens the door for future advancements in telemedicine and broader public health initiatives, promoting preventive care through data-driven insights and improving overall health outcomes.

The rest of the paper is organized as follows. Section 2 presents a related work of various references and briefly describes them. Section 3 defines an overview of deep learning using skin disease, while section 4 Describes the overview dataset used. Finally, section 5 includes the conclusion and future work on Skin disease prediction.

II. RELATED WORK

This section provides a survey of contemporary traditional methods, machine learning, and deep learning techniques employed for detecting and classifying skin diseases based on image characteristics.

Hritwik Ghosh et al. leverage AI and deep learning models, including VGG16, ResNet50, and DenseNet121, for efficient skin cancer detection, mitigating class imbalance using class weighting. They highlighted the superior performance of hybrid models,[3],[5] combining VGG16 and ResNet50, as support tools for dermatologists. Further research was suggested to enhance model robustness in clinical settings. Additionally, they proposed expanding these methods to other diseases for broader healthcare impact.

Parvathaneni Naga Srinivasu et al. describes a skin disease classification model using MobileNet V2 and LSTM, achieving 85.34% accuracy with minimal computational power, making it suitable for lightweight devices. [1] The model outperformed traditional approaches like CNN and FTNN, particularly in efficiently identifying affected regions.[6] LSTM enhances prediction by maintaining stateful information, though performance declines under poor illumination. This approach is intended to supplement, rather than replace, existing diagnostic methods.

Soujenya Voggu et al. highlighted the need for automated CAD systems to improve skin disease diagnosis by addressing challenges in feature extraction due to similar visual characteristics among conditions. They compared traditional methods with deep learning models like CNN, which automatically [7] learn and extract features more effectively. The study emphasized that deep learning, using models like VGG16 and Inception v3, offers superior accuracy for skin disease classification.

Muddasar Abbas et al. proposed using deep learning models like Sequential CNN, DenseNet-121, and ResNet-50 to classify skin diseases using the HAM10000 dataset. Their Sequential CNN model with seven [4] convolutional layers achieved 98% accuracy, outperforming DenseNet-121 and ResNet-50, which had 89% and 84% accuracy, respectively. The study emphasizes improving skin disease diagnosis with AI, allowing dermatologists to verify and refine the model's predictions in the future.

Oluwayemisi Jaiyeoba et al. proposed an ensemble machine learning model for classifying [8] Erythemato-Squamous Diseases[(ESD) using five classifiers, achieving a remarkable accuracy of 99.30%. The Support Vector Classifier performed the best individually with an accuracy of 98.61%. Their study highlights the importance of early diagnosis and accurate treatment to effectively manage skin diseases

Shagun Sharma et al. developed a deep learning model utilizing the Inception V3 feature extractor for predicting and classifying vitiligo skin disease, achieving up to 99.9% accuracy with a random forest classifier. Their study emphasizes the model's potential to assist dermatologists in early detection and treatment, highlighting the need for expanded datasets and further research for improved accuracy.

Alexander H. Thieme et al. developed the MPXV-CNN, an image-based deep convolutional neural network for early detection of monkeypox virus (MPXV) skin lesions, utilizing a dataset of 139,198 images. The model demonstrated [3],[7] high sensitivity and specificity, with robust performance across various skin tones and body regions. A web-based app was created for accessible patient guidance, enhancing the potential for MPXV outbreak mitigation.

Matthew Groh et al proposed a large-scale digital experiment, in which dermatologists and primary-care physicians were assessed for their diagnostic accuracy on inflammatory skin diseases using 364 images of 46 conditions. Specialists achieved a 38% accuracy, while generalists [10],[2] scored only 19%, with both groups performing worse on dark skin images. Although decision support from a fair deep learning system improved diagnostic accuracy by over 33%, it exacerbated the accuracy gap for generalists across different skin tones, illustrating that increased accuracy doesn't necessarily address bias.

Evgin Goceri et al. define a modified MobileNet model for diagnosing five common skin diseases using mobile devices. It incorporates dilated convolutions, [11] LeakyReLU, and a novel hybrid loss function to enhance classification accuracy. The model, trained on public datasets (DermWeb, DermNet, Dermatoweb, DermQuest), achieved 94.76% accuracy, outperforming other lightweight architectures.

Oussama El Gannour et al. proposed a novel approach to tackle the imbalance of class in skin disease prediction using class weighting and [12] transfer learning with EfficientNetV2L. Their method, tested on the ISIC 2018 dataset, significantly improved model performance, especially for rare disease categories. Future work suggests exploring additional data balancing techniques and incorporating multi-modal data for further enhancements.

III. DEEP LEARNING USING SKIN DISEASE PREDICTION

a) Deep Learning: Deep learning models effectively the features that assist in understanding complex patterns and accurately precisely. Deep learning has transformed medical imaging by offering automated solutions that improve diagnostic accuracy and efficiency. Traditional skin disease diagnosis, dependent on dermatologists, can be subjective and time-consuming. [13] Convolutional Neural Networks (CNNs) effectively automate this process by extracting detailed features from medical images.

Deep learning is a subset of Machine learning, it is similar and consists of three layers, and every layer is interconnected to each other either forward or backward propagation:

- ***Input layer:*** It is the first layer, which is used to take input and consists of n^{th} nodes of input.
- ***Hidden layer:*** one or more hidden layers, which is the product of input and weights. It defines the feature extraction on it.
- ***Output layer:*** It is used to define the measure difference between actual value and predicted values.

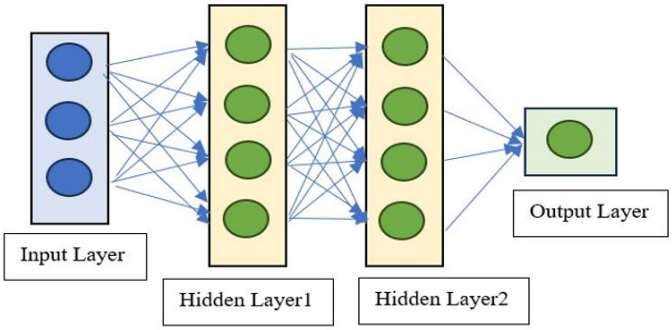

Fig 1. Overview of Deep Learning Model

b) MobileNet V2 Architecture: MobileNet V2, a Convolutional Neural Network (CNN) model, is designed for efficient image classification with lower computational requirements, making it ideal for mobile and low-capability devices. [14] MobileNet V2 simplifies the structure by using depth-wise and point-wise convolutions, which balance between accuracy and latency effectively. The architecture uses abstraction layers and standard rectified linear units (ReLU) to minimize input image dimensionality and internal representations

c) LSTM Architecture: LSTM (Long Short-Term Memory) enhances the performance by maintaining state information across image classification generations. [15] It includes input, output, and forget gates within memory cells, [16] which manage the hidden and cell states for sequence learning.

LSTM equation:

- Input Gate: $\alpha_t = \sigma(itW_\alpha + \gamma_{t-1}W_{\gamma\alpha} + cst_{t-1}W_{c\alpha} + \alpha_{\text{bias}})$.....Equation (1)
- Output Gate: $\beta_t = \sigma(itW_\beta + \gamma_{t-1}W_{\gamma\beta} + cstW_{c\beta} + \beta_{\text{bias}})$.....Equation (2)
- Forget Gate: $f_t = \sigma(itW_f + \gamma_{t-1}W_{\gamma f} + cstW_{cf} + f_{\text{bias}})$.....Equation (3)
- Cell State: $cst = f_t \cdot cst_{t-1} + \alpha_t \cdot \tanh(itW_{ics} + \gamma_{t-1}W_{\gamma cs} + cs_{\text{bias}})$.....Equation (4)
- LSTM Outcome: $\gamma_t = \beta_t \cdot \tanh(cst_{t-1})$.....Equation (5)

Fig 2. Equation of LSTM model [1]

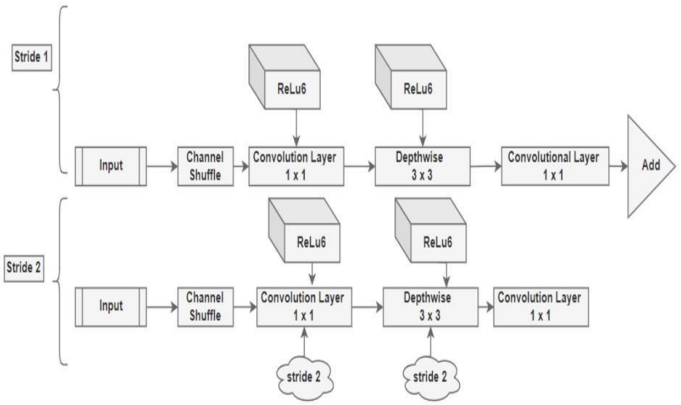

Fig 3. Architecture of Mobile Net v2 [2]

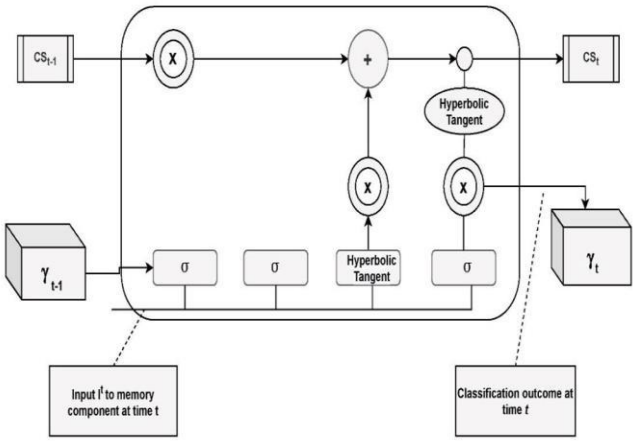

Fig 4. Architecture of LSTM component [2]

IV. DATASET DESCRIPTION

The dataset is essential for training our proposed neural networks for automated diagnosis. [17] The real-world dataset used in this research includes both training and testing data, encompassing a variety of skin conditions. The dataset has been structured to facilitate a [18] comprehensive evaluation of our model's performance.

- **Total Images:** The dataset contains dermatoscopic images of over 10,000 that are collected from individuals worldwide.
- **Image Dimensions:** Each image is resized to a target size of 224 × 224 pixels to standardize input for the neural network.

The dataset includes images categorized into nine different types of skin conditions:

- Actinic Keratosis
- Atopic Dermatitis
- Benign Keratosis
- Dermatofibroma
- Melanocytic Nevus
- Melanoma
- Squamous Cell Carcinoma
- Tinea Ringworm Candidiasis
- Vascular Lesion

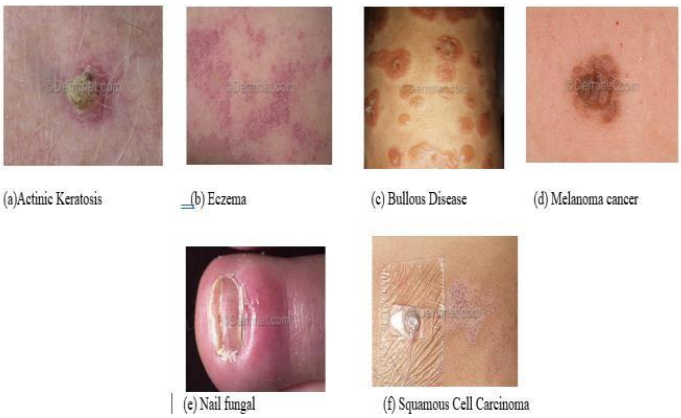

Fig 5. Overview description of DermNet Dataset [19]

V. CONCLUSION AND FUTURE WORK

Future improvements can be achieved by integrating a bidirectional LSTM, which could further enhance the model's performance. The practical implementation of the model involves a front end designed with Android Studio, SSDLite, or DeepLabv3+, alongside a business model built over Kaggle. While significant progress has been made, several shortcomings remain. The model's precision drops to below 80% when tested with images captured under poor lighting conditions, different from those used during the training and testing phases.

The model is optimized for computational efficiency and designed to function on lightweight devices. The combination of MobileNetV2 and LSTM requires a substantial number of parameters to enhance accuracy. However, the input images and corresponding outputs from this model demonstrate minimal variability, which may limit the exploration of all possible patterns during assessment. Despite challenges in residual connections, the model attains high accuracy with minimal computational effort. Future advancements could introduce self-learning capabilities and the ability to leverage prior knowledge, thereby reducing the need for extensive training. Furthermore, automating the model to evaluate the impact of extracted features and integrating randomization mechanisms would be beneficial. Skin disease classification using LSTM and MobileNetV2 demonstrates superior accuracy compared to previous models.

As compared to VGG 16 (76.54%), RestNet 50 (93.76%), Sequential CNN (98.67%), and DenseNet-121 (94.54%), but combined LSTM and Mobile Net v2 an accuracy of (98.87%). Utilizing the Real-world dataset, the proposed method achieved high accuracy, outperforming these models. Its ability to identify affected regions more quickly, with nearly half the computations of the conventional Mobile Net model, minimizes computational demands.

Table 1. Difference accuracy of various models

Reference Number	Model Used	Dataset	Accuracy
[1]	VGG16, ResNet50, hybrid models (VGG16 + ResNet50)	ISIC 2017 dataset	74.83%
[2]	MobileNet V2, LSTM	HAM10000	83.34%
[3]	CNN, VGG16, Inception v3	ISBI 2016, PH2 dataset	91.24%
[4]	Sequential CNN, ResNet101, DenseNet201	HAM10000	98.28%
[5]	AdaBoost classifier, Random Forest	129,450 clinical photos	95.30%
[6]	Hybrid models	DermNet and DermQuest	93.74%
[7]	MPXV-CNN, Transformer	ISIC 2019 Challenges Data Set	91.57%
[8]	NewU-Net	ISIC2018, ISIC2016 datasets	95.98%
[9]	EfficientNetV2, transfer learning	Dermoscopy images	97.65%
[10]	Modified-MobileNet (dilated convolutions, LeakyReLU, hybrid loss function)	DermWeb, DermNet, Dermatoweb, DermQuest	94.76%

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Abstract:
Deep learning models excel in recognizing complex
patterns by learning relevant features effectively. This study
introduces a computerized approach to classifying skin diseases using a combination of Mobile Net V2 and Long Short-Term Memory (LSTM) networks. Mobile Net V2 demonstrates high accuracy and efficiency on lightweight computational devices. The model maintains stateful information for accurate predictions and uses a grey-level cooccurrence matrix to assess disease progression. The model's performance was evaluated in comparison to other top models, such as Fine-Tuned Neural Networks (FTNN), Convolutional Neural Networks (CNN), Very Deep Convolutional Networks for Large-Scale Image Recognition by the Visual Geometry Group (VGG), and an improved CNN architecture. Utilizing the real-world dataset, the method achieved high accuracy, outperforming these models. Its ability to identify affected regions more quickly, with nearly half the computations of the conventional Mobile Net model, minimizes computational demands.

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