

Machine Learning & Neural Networks

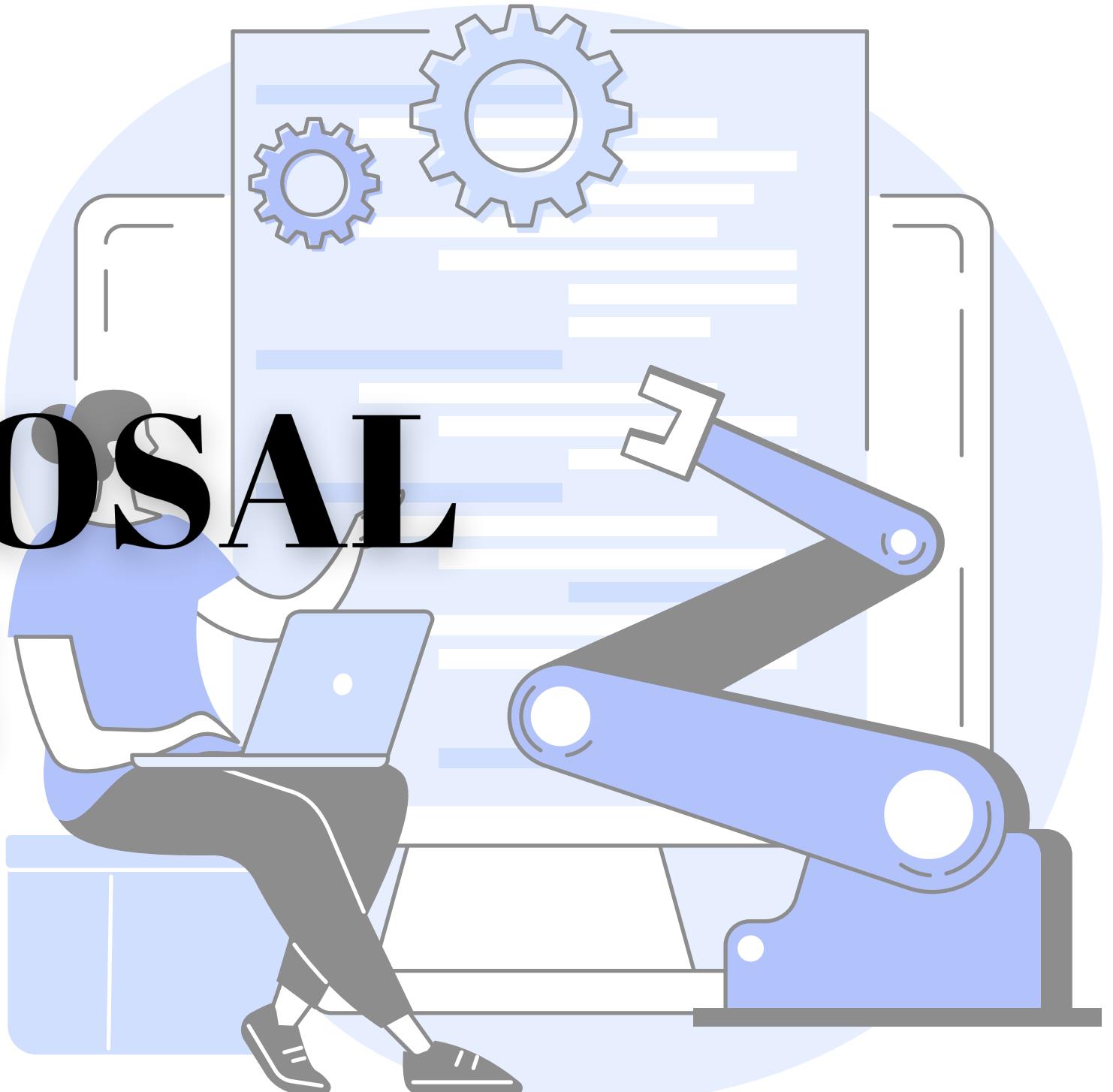
6 May 2024

PROJECT PROPOSAL PRESENTATION

Deep Learning On Public Dataset

Presented By

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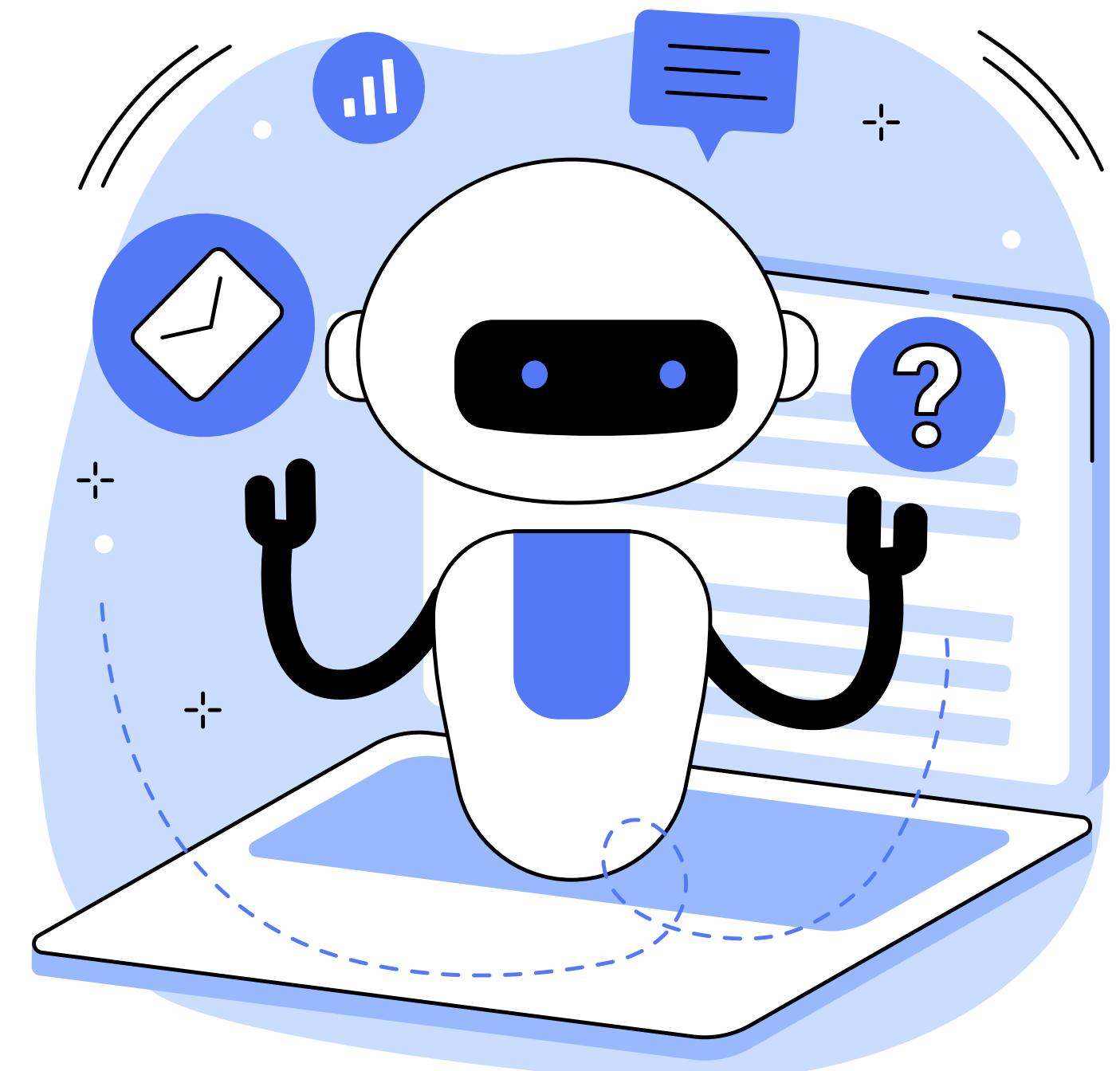


PROJECT OVERVIEW

Enhancing Vehicle Classification & Recognition with Deep Learning

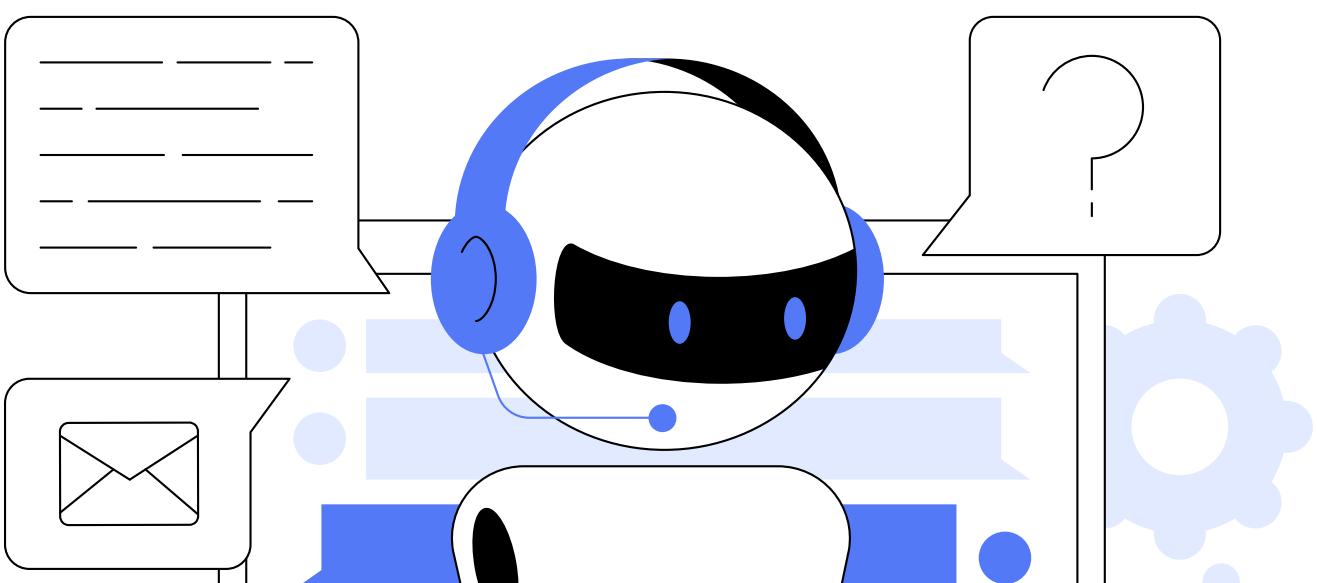
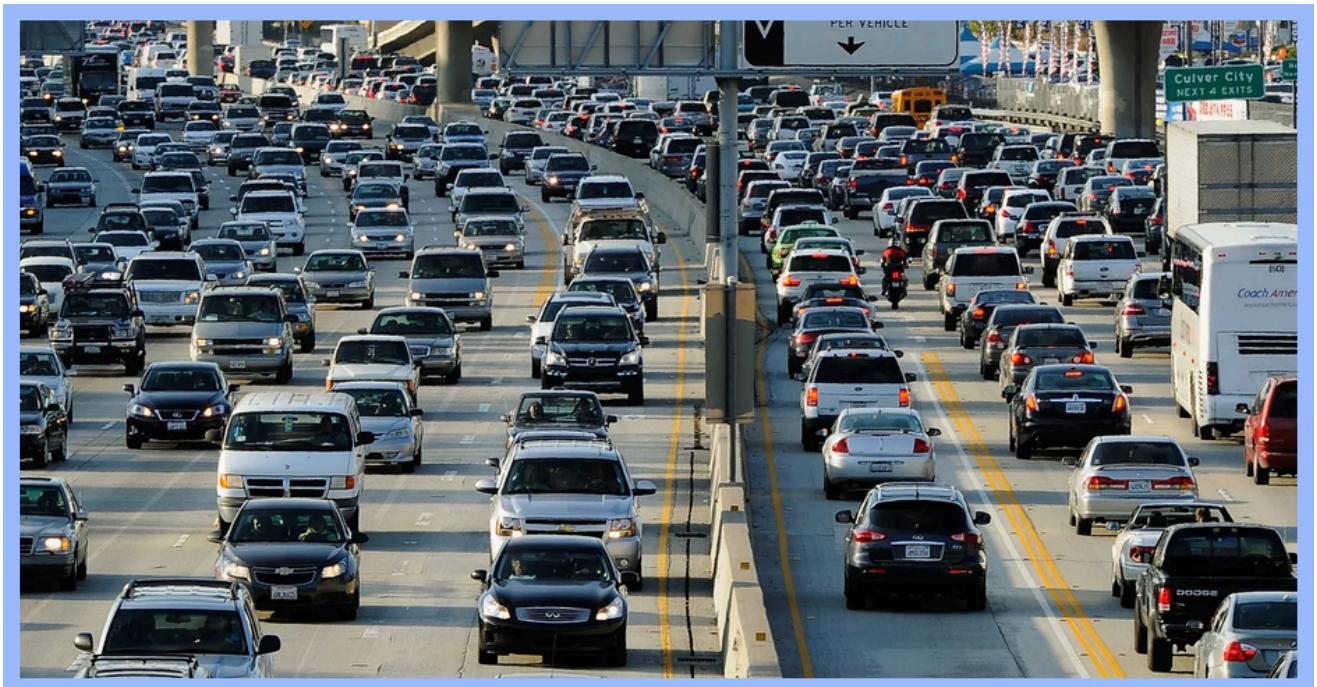
The primary idea of this project is to develop a robust system that can classify and recognize vehicles in images.

This involves two main tasks: vehicle classification and vehicle recognition (object detection). By combining image classification with object detection techniques, we aim to build an efficient model capable of accurately identifying various types of vehicles and localizing them within images.



PROBLEM STATEMENT

In recent years, advancements in deep learning have revolutionized computer vision applications, particularly in the **domain of vehicle classification and recognition**. Despite significant progress, there remains a critical need to address key challenges and gaps in this field. The problem at hand revolves around the **accuracy and efficiency** of vehicle classification and recognition systems based on deep learning models.



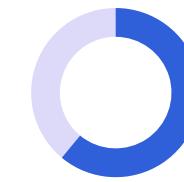
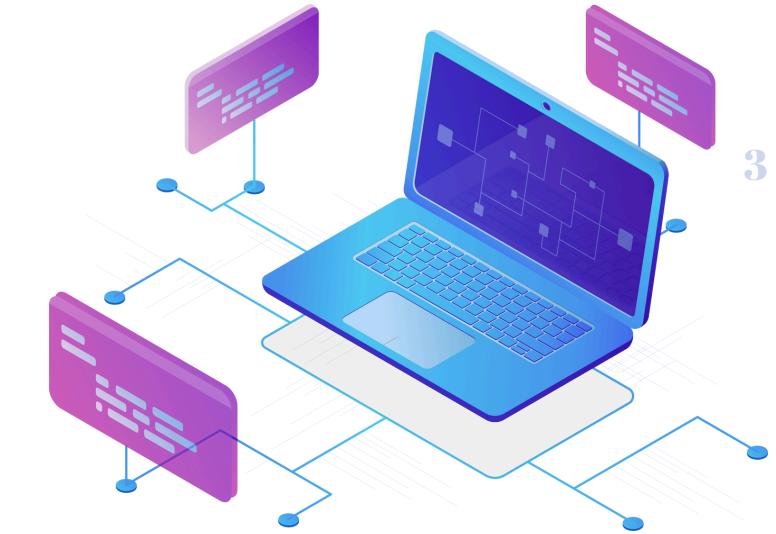
PROBLEM STATEMENT

Vehicle classification and recognition are crucial tasks with various real-world applications, including traffic monitoring, surveillance, and autonomous driving.



PROBLEM STATEMENT

Current approaches often struggle with the following



Multi-Class Classification

Existing methods for vehicle classification do not always generalize well across diverse vehicle types, including cars, trucks, vans, motorcycles, etc.



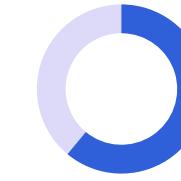
Fine-Grained Attribute Recognition

While some models can identify broad vehicle categories, they often fall short in recognizing finer attributes such as vehicle make, model, color, and license plate details.



Real-Time Object Detection

Object detection algorithms used for vehicle localization and recognition may not consistently meet the speed and accuracy requirements necessary for practical deployment in real-time scenarios like traffic surveillance or autonomous driving.



Robustness to Environmental Variability

Variations in lighting conditions, weather, and occlusions pose significant challenges for existing vehicle recognition systems, affecting their reliability and performance.

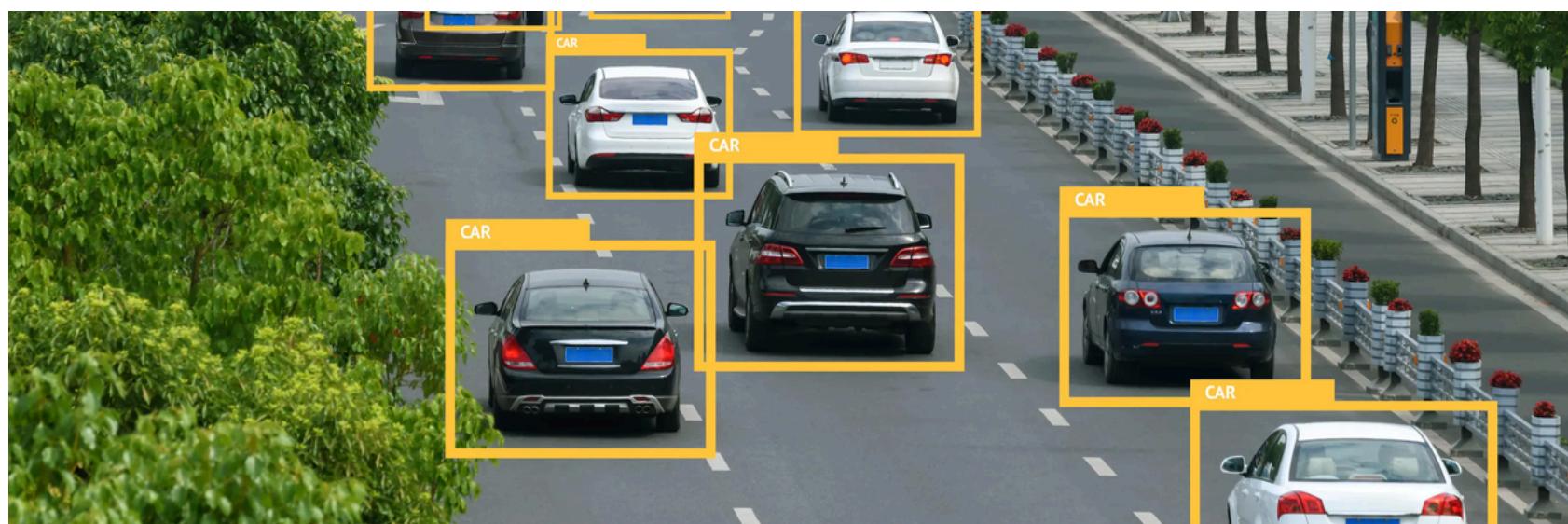
PROBLEM STATEMENT

The limitations identified underscore the critical need for research aimed at

Developing more robust deep learning architectures tailored specifically for accurate and efficient vehicle classification across diverse categories.

Enhancing fine-grained attribute recognition capabilities within vehicle detection models to extract detailed information crucial for various applications.

Optimizing object detection algorithms to achieve real-time performance while maintaining high accuracy and robustness in challenging environments.



AIMS & OBJECTIVES

Developing a vehicle classification model that can identify different vehicle types.

1

Implementing an object detection system to localize and recognize vehicles along with extracting detailed attributes.

2

Deploying the trained model for real-time inference, potentially integrating it into a practical application or system.

3

Collecting and preprocessing a diverse dataset of vehicle images suitable for training.

1

Training a CNN-based classifier using transfer learning for vehicle classification.

2

Annotating vehicle images with bounding boxes and attributes for object detection.

3

Implementing and training an object detection model capable of recognizing vehicles

4

Evaluating the model's performance using appropriate metrics like accuracy and etc.

5

PROJECT MOTIVATION

As a resident of Singapore, a dynamic urban environment known for its advanced transportation infrastructure, I have personally witnessed the increasing importance of automated vehicle recognition systems in enhancing safety, efficiency, and overall urban mobility.

The motivation behind this project stems from the growing demand for intelligent systems capable of analyzing and understanding visual data.

Vehicle classification and recognition have numerous applications in transportation, public safety, and urban planning. By leveraging deep learning techniques, we can develop efficient solutions that can contribute to enhanced traffic management, security surveillance, and the development of autonomous vehicles.



RELATED PROJECTS

In the domain of automated vehicle recognition using deep convolutional neural networks (DCNN), several notable projects and research papers have contributed to advancements in this field. Some of the related work includes:



1. “Vehicle Detection and Classification in Aerial Images using Convolutional Neural Networks” by Chih-Yi Li and Huei-Yung Lin
2. “Automated Vehicle Recognition with Deep Convolutional Neural Networks” by Yaw Okyere, Adugamfi, Sampson Kwasi Asare, Anuj Sharma, and Tienaaah Titus
3. “Vehicle Classification with Deep Learning” by W. Maungmai and C. Nuthong

SUMMARY OF PROJECT NO. 1

“Vehicle Detection and Classification in Aerial Images using Convolutional Neural Networks” by Chih-Yi Li and Huei-Yung Lin

The project focuses on developing a technique for vehicle detection and classification from aerial images using deep learning, specifically a modified Faster R-CNN framework. The key contributions of this project include proposing a new dataset (VAID - Vehicle Aerial Imaging from Drone) annotated with seven common vehicle categories, and comparing the performance of their method with existing network architectures and datasets commonly used in this domain.

Vehicle Detection and Classification in Aerial Images using Convolutional Neural Networks

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Keywords: Aerial Image, Convolutional Neural Network, Vehicle Detection.

Abstract: Due to the popularity of unmanned aerial vehicles, the acquisition of aerial images has become widely available. The aerial images have been used in many applications such as the investigation of roads, buildings, agriculture distribution, and land utilization, etc. In this paper, we propose a technique for vehicle detection and classification from aerial images based on the modification of Faster R-CNN framework. A new dataset for vehicle detection, VAID (Vehicle Aerial Imaging from Drone), is also introduced for public use. The images in the dataset are annotated with 7 common vehicle categories, including sedan, minibus, truck, pickup truck, bus, cement truck and trailer, for network training and testing. We compare the results of vehicle detection in aerial images with widely used network architectures and training datasets. The experiments demonstrate that the proposed method and dataset can achieve high vehicle detection and classification rates under various road and traffic conditions.

1 INTRODUCTION

In recent years, due to the popularity of unmanned aerial vehicles (UAVs), the acquisition of aerial images has become more convenient. A large volume of aerial images can be obtained very quickly. The use of big data is a trend of the future research related to aerial image analysis. The techniques for aerial images has been adopted in many applications such as the investigation of roads, buildings, agriculture distribution, and land utilization, etc. One specific importance is the detection of vehicles from aerial

images has also been used for the detection of special buildings or large venues in the past few decades, especially for the military purposes such as aircraft and runway detection. Due to the advances of deep learning techniques in recent years, object detection can be achieved under complex backgrounds and a variety of application scenarios. Thus, it becomes more feasible to use aerial images for the detection and classification of vehicles.

The methods for vehicle detection in aerial images are generally divided into two categories, the traditional approaches and the machine learning task

CRITICAL EVALUATION

Strengths

- Adoption of a modified Faster R-CNN framework using ResNet101 for feature extraction, which has shown improved performance compared to standard architectures.
- Detailed analysis and comparison with existing datasets like VEDAI demonstrate the effectiveness of the proposed method under various road and traffic conditions.
- Experimentation with different activation functions (softplus, ELU, ReLU) to optimize model performance.

Weaknesses

- The study could benefit from a more extensive analysis of model generalization to challenging scenarios beyond the tested conditions.
- The dataset imbalance across different vehicle classes (as noted in Table 4) could potentially impact the model's ability to generalize well across all categories.
- The project evaluation could be enhanced by including qualitative analysis and visual demonstrations of detected vehicle instances in challenging scenarios.

METHODOLOGY & RESULTS

- Adoption of a modified Faster R-CNN architecture with ResNet101 as the feature extraction backbone.
- Preprocessing of VEDAI dataset for comparison purposes, focusing on vehicle-related categories.
- Experimentation with different activation functions in the Faster R-CNN framework to optimize model training and performance.
- Comparison between training with VEDAI and VAID datasets shows superior performance of the proposed method when using VAID for vehicle detection and classification.
- Evaluation across different testing scenarios (Scenes A-D) highlights the robustness of the proposed method in various road and traffic conditions.
- Improvement in mean Average Precision (mAP) with the modified Faster R-CNN architecture compared to the original framework, particularly notable with the adoption of ReLU activation function.

SUMMARY OF PROJECT NO. 2

“Automated Vehicle Recognition with Deep Convolutional Neural Networks” by Yaw Okyere, Adu-Gyamfi, Sampson Kwasi Asare, Anuj Sharma, and Tienaaah Titus

The project focuses on developing an automated vehicle recognition system using Deep Convolutional Neural Networks (DCNNs). The aim is to classify vehicles according to the Federal Highway Administration's (FHWA) 13 vehicle types using video data from CCTV cameras. The system utilizes DCNNs for object localization and classification, trained on large datasets to achieve high accuracy in vehicle recognition under challenging real-world conditions such as varying traffic volumes, lighting, and video resolutions.

Automated Vehicle Recognition with Deep Convolutional Neural Networks

Yaw Okyere Adu-Gyamfi, Sampson Kwasi Asare, Anuj Sharma, and Tienaaah Titus

In recent years there has been growing interest in the use of nonintrusive systems such as radar and infrared systems for vehicle recognition. State-of-the-art nonintrusive systems can report up to eight classes of vehicle types. Video-based systems, which arguably are the most popular nonintrusive detection systems, can report only very coarse classification levels (up to four classes), even with the best-performing vision systems. The present study developed a vision system that can report finer vehicle classifications according to FHWA's scheme and is also comparable to other nonintrusive recognition systems. The proposed system decoupled object recognition into two main tasks: localization and classification. It began with localization by generating class-independent region proposals for each video frame, then it used deep convolutional neural networks to extract feature descriptors for each proposed region, and, finally, the system scored and classified the proposed regions by using a linear support vector machines template on the feature descriptors. The precision of the system varied by vehicle class. Passenger cars and SUVs were detected at a precision rate of 95%. The precision rates for single-unit, single-trailer, and double-trailer trucks ranged between 92% and 94%. According to receiver operating characteristic curves, the best system performance can be achieved under free flow, daytime or nighttime, and with good video resolution.

Transportation agencies seeking to optimize traffic mobility and

fessionals must identify the appropriate technique and agency's data collection needs.

One of the many data needs of transportation agencies is vehicle type classification (3). Accurate classification data are needed for traffic operation, pavement design, and transportation planning. For example, the total number of trucks in a state or region is useful for computing the corresponding parameters needed to estimate the capacity of that road network. Additionally, the geometric design characteristics (e.g., horizontal alignment, curb heights) are dictated by the type of vehicles that will use such roadways (6). Under federal law, the Highway Performance Monitoring System, which monitors traffic volume and speed, provides classified vehicle counts on freeways and highways to the FHWA every year (7). Vehicle classification data are therefore critical to the effective management of transportation systems.

Many techniques for acquiring vehicle type information have been discussed in the literature, and prominent among them is the application of image processing techniques such as neural networks and support vector machines for vehicle-based classification systems. In most instances, classification is based on the dimensions of vehicles. Lai et al. demonstrated the feasibility of accurate vehicle dimensions by using a set of functions (8). Although they were able to estimate the dimensions to within 10% in every instance, their method had a significant limitation in that it required

CRITICAL EVALUATION

Strengths

- Advanced Technology: Leveraging DCNNs allows for robust feature learning and classification, surpassing traditional machine vision techniques.
- Accurate Classification: Achieving precision rates of 82% to 100% for different vehicle classes demonstrates the effectiveness of the approach.
- Robustness to Conditions: The system's ability to handle challenging conditions like varying traffic and lighting conditions showcases its practical utility.

Weaknesses

- Some vehicle classes, like vans and pickups, have lower precision rates due to limited training data, affecting system performance.
- Sensitivity to Occlusions: Occlusions by larger vehicles impact the system's recall rates, especially for passenger cars.
- Complexity and Computation: DCNNs are computationally expensive, requiring substantial processing power and time for model training and inference.

METHODOLOGY & RESULTS

- Utilizes Selective Search for generating region proposals.
- Employs DCNNs for extracting feature descriptors from proposed regions.
- Implements linear SVMs for classifying vehicle types based on extracted features.
- Supervised pretraining on a large dataset (ILSVRC2012) followed by domain-specific fine-tuning on CCTV data.
- Achieved average precision rates ranging from 82% to 100% across different vehicle classes.
- Notable accuracy in recognizing motorcycles and buses (100% precision).
- Challenges observed in distinguishing van and pickup variants (82% precision).
- System performance evaluated under different traffic, lighting, and video resolution conditions.
- Best performance under free-flow daytime conditions with good video quality.

SUMMARY OF PROJECT NO. 3

“Vehicle Classification with Deep Learning” by W. Maungmai and C. Nuthong

The paper explores the application of Convolutional Neural Networks (CNNs) to address challenges in vehicle recognition within surveillance videos. It specifically focuses on vehicle classification tasks, including vehicle type and color classification. The study aims to improve the accuracy of these classification modules using CNN-based approaches.

Vehicle Classification with Deep Learning

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Nowadays, there are many traffic surveillance which are installed in almost every city to record traffic. The surveillance system is used for various , e.g. vehicles searching and real-time traffic g, etc. For the searching purpose, the system can be policeman such as outlaw's vehicle identification in pically, the officers manually identify the vehicle in video according to its appearances. Although the of this approach is good, it is time-consuming and o faults due to human fatigue for long duration oreover, hiring employees is costly. Recently, there l machine learning methods which can be applied to chicles, e.g. Fuzzy Logic, Decision Tree, Adaboost, Forest, Neural Network, etc. Convolutional Neural (CNN) is also one of such methods. CNN is a type of rning which is in the category of the neural network. od is very well-known in image recognition field at it because of its performance. In the proposed vehicle ion, there are two vehicle characteristics, i.e. types s. Types consist of four classes while colors consist of es. CNN is then used as to classify vehicle images. rimental results show that CNN can achieve high nce in real-world applications.

ards-vehicle classification; size classification; color ion; deep learning; convolutional neural network

I. INTRODUCTION

in order to reduce memory and computatio However, the combinations of four or more featur make classification accuracy increases. R. Feris constructed a system which could search for ' surveillance videos. They proposed a new class Motionlet. The classifier was a detector based on learning [3]. The main task of Motionlet was c twelve different direction of vehicles. As a result, achieve 87% accuracy rate. S. B. Changalasetty used an artificial neural network as a classi classified vehicles into two categories, i.e. big Their results achieved more than 90% accuracy Gislason et al. [5] compared the perfor classification among various classifiers, i.e. regre bagging, boosting, and random forest. In their expe methods gave results which were comparable to . However, random forest was chosen since two re shorter learning time compared to other me required no guidance. Saripan et al. [6], [7] pr vehicle search system. The system used a surveill as input and allowed user to select vehicle charac order to search for specific vehicles. The au proposed Tree-based vehicle classification in categorize vehicles from the video. In their expe classification worked well when combined with th

In recent decades, there is another method Learning [8] which can be used in classification

CRITICAL EVALUATION

Strengths

- Leveraging CNNs for vehicle classification tasks demonstrates the cutting-edge use of deep learning in real-world applications.
- The paper compares its proposed CNN-based method with previous techniques like decision trees, random forests, and densely DNN, showcasing improvements in accuracy.
- Provides comprehensive experimental setups, including dataset characteristics, model architectures, and hyperparameters.

Weaknesses

- Stability and Variability: The results indicate some variability and instability in performance metrics (e.g., standard deviations), suggesting the need for further optimization of CNN hyperparameters.
- Limited Discussion on Challenges: Although the proposed CNN approach shows promising results, the paper could benefit from discussing specific challenges faced in real-world scenarios (e.g., occlusions, lighting conditions).

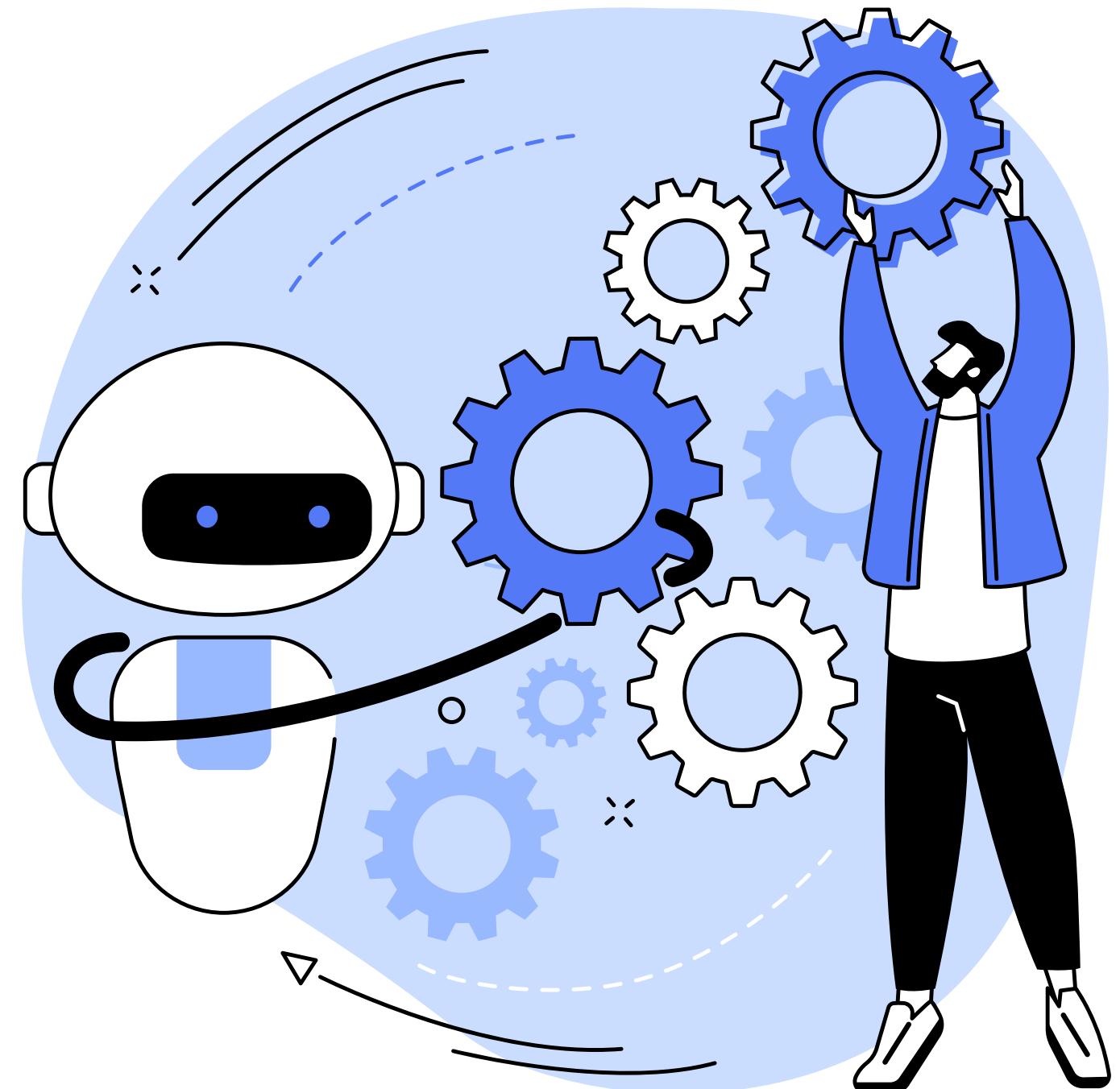
METHODOLOGY & RESULTS

- The proposed CNN architecture includes two convolutional layers followed by pooling layers and fully connected layers for vehicle classification.
- Utilizes a specific dataset with extracted vehicle images for training and testing CNN models. Evaluates performance metrics like accuracy for vehicle type and color classification.
- Achieves superior accuracy in vehicle type classification (84.65%) compared to existing methods like decision trees and random forests.
- Identifies opportunities for enhancing color classification accuracy (70.09%) through further refinement of CNN hyperparameters and model structures.

MOTIVATION ANALYSIS

Generalization and Robustness

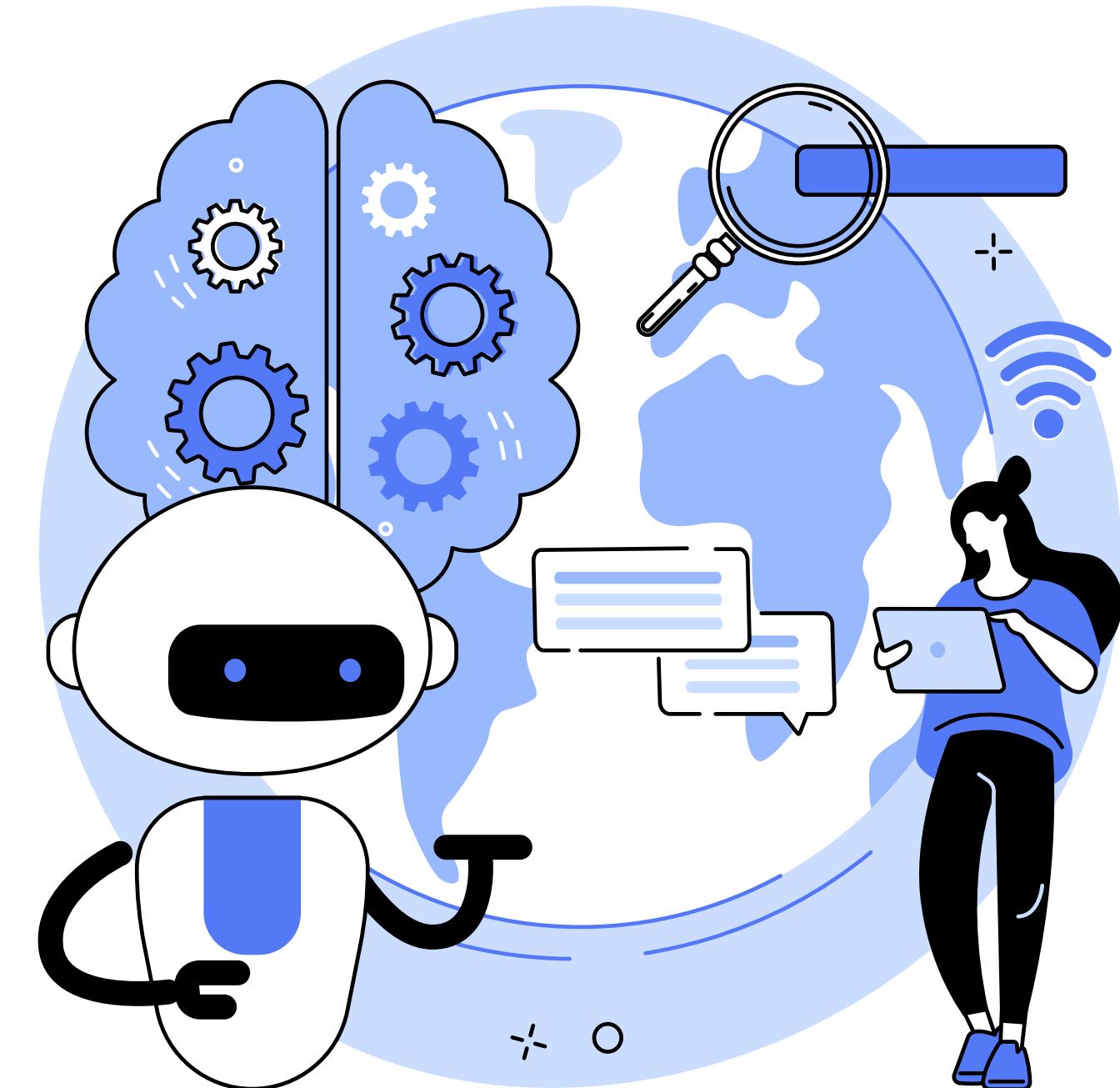
Existing approaches often struggle with generalization across diverse vehicle types and robustness to environmental variability (e.g., lighting conditions, occlusions). By developing more robust deep learning architectures tailored specifically for accurate and efficient vehicle classification, we aim to overcome these challenges.



MOTIVATION ANALYSIS

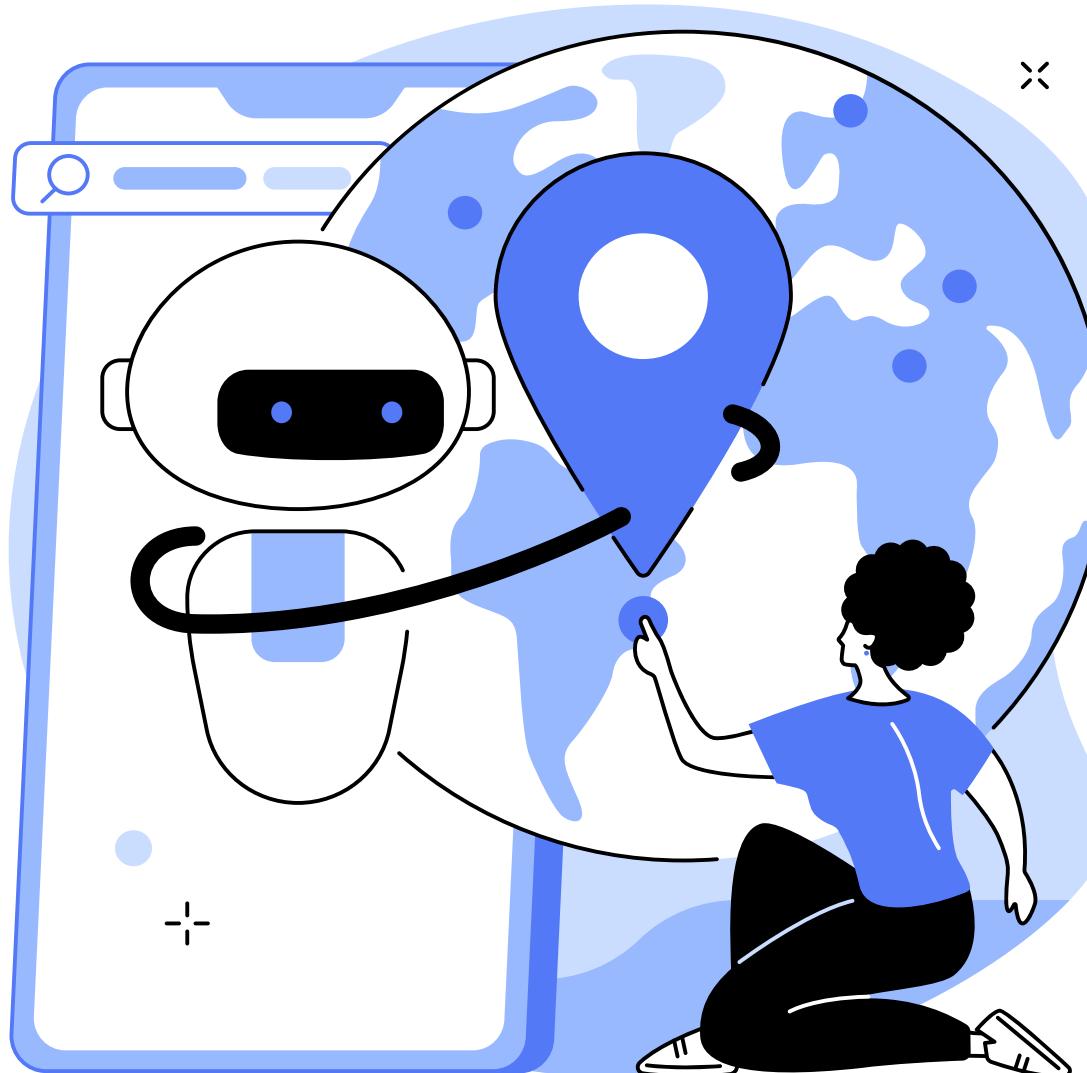
Fine-Grained Attribute Recognition

Current models often fall short in recognizing finer attributes such as vehicle make, model, color, and license plate details. Enhancing fine-grained attribute recognition within vehicle detection models is crucial for various applications, including law enforcement and traffic management.



JUSTIFICATION ON DOMAIN & USER

Relevance to Real-World Applications



Vehicle classification and recognition have numerous practical applications in transportation, public safety, and urban planning. The ability to accurately identify and localize vehicles is crucial for tasks like traffic monitoring, surveillance systems, and the development of autonomous vehicles. These applications are particularly relevant in dynamic urban environments like Singapore, where advanced transportation infrastructure requires efficient automated systems for traffic management and safety.

JUSTIFICATION ON DOMAIN & USER

Technological Advancements in Deep Learning



Recent advancements in deep learning, especially in the field of computer vision, have significantly improved the accuracy and efficiency of vehicle recognition systems. Deep convolutional neural networks (DCNNs) excel at learning complex features from images, making them well-suited for tasks like vehicle classification and object detection.

JUSTIFICATION ON DOMAIN & USER

Growing Demand for Intelligent Systems



There is a growing demand for intelligent systems capable of analyzing visual data in real-time to enhance safety, efficiency, and overall urban mobility. Automated vehicle recognition systems contribute significantly to achieving these goals by enabling better traffic management, security surveillance, and the development of autonomous driving technologies.

CONCLUSION

The project proposal aims to develop robust deep learning architectures for vehicle classification and recognition, addressing key challenges in generalization across diverse vehicle types, fine-grained attribute recognition, and real-time performance.





**THANK YOU FOR
LISTENING!**