You should submit a draft literature survey for your project. This should be a document covering at least 4-6 examples of previous work or academic literature.

Examples of types of literature you might want to include:

* Examples of projects that are similar to your own (these can be the same as those used in your proposal).
* Techniques and methods that you plan to use. These could be software libraries, algorithms, or research methodologies.
* Research studies that show the effectiveness of the project you intend to create (for example, if you are doing a project on educational technology, a psychological or educational study showing that the techniques you are using are effective for teaching).

This literature can include academic papers and books. It can also include online articles and websites, but in that case, you should also explain why you consider them credible sources.

You should evaluate the literature and explain how it contributes to your project, or how it demonstrates the gaps that your project intends to fill.

The report should be in PDF format, up to 6 pages (minimum font size 11pt, minimum margin 2cm). There is a word limit in the summative assessments of 2500 words for your literature review, so it is a good idea to try to stick within this. You may include additional pages of images and citations.

You should, if appropriate, use visual materials, for example, images and diagrams from the literature you are citing. You might also want to include tables that compare different examples of prior work.

All work discussed should be [properly cited and referenced](https://onlinelibrary.london.ac.uk/support/referencing) in [ACM format](https://onlinelibrary.london.ac.uk/sites/default/files/files/guides/ACMGuide.pdf).

Grading Criteria Overview

You will be marked according to the following criteria:

1. Does the report display knowledge of the area of study, previous work and academic literature?
2. Does the report critically evaluate the previous work and/or academic literature?
3. Does the report use proper citation and referencing?

**CM3070 Final Year Project**

**Literature Review**

The development of automated vehicle classification and recognition systems has significant implications for transportation, public safety, and urban planning. This literature review examines key works and methodologies relevant to creating robust deep learning models for these tasks. The review highlights advancements in the field and identifies the gaps that the proposed project aims to fill.

One notable contribution is the study by Chih-Yi Li and Huei-Yung Lin, titled **"Vehicle Detection and Classification in Aerial Images using Convolutional Neural Networks".** This research focuses on developing a sophisticated method for vehicle detection and classification from aerial images, utilizing a modified Faster R-CNN framework.

Li and Lin's project presents several critical advancements. Firstly, they propose a new dataset named Vehicle Aerial Imaging from Drone (VAID), which is meticulously annotated with seven common vehicle categories. This dataset enhances the variety and specificity of vehicle images available for training deep learning models, addressing a gap in existing datasets that often lack comprehensive annotations.

Additionally, the study conducts a comparative analysis between their proposed method and existing network architectures and datasets commonly used in this domain. By implementing a modified Faster R-CNN framework with ResNet101 as the feature extraction backbone, the authors demonstrate improved performance in vehicle detection and classification. This framework's adoption is particularly noteworthy due to its advanced capability in feature extraction, which significantly outperforms standard architectures.

**Methodology**

The methodology employed in this study involves several innovative steps:

1. **Framework Modification:** The authors adopt a modified Faster R-CNN architecture, incorporating ResNet101 for feature extraction. This modification leverages the superior performance of ResNet101 in capturing detailed features from images.
2. **Dataset Preprocessing:** For comparative purposes, the VEDAI dataset is preprocessed, focusing specifically on vehicle-related categories. This preprocessing ensures that the comparison between different datasets is fair and targeted.
3. **Activation Function Experimentation:** To optimize model training and performance, the authors experiment with different activation functions within the Faster R-CNN framework. These include softplus, ELU, and ReLU, each tested to determine the most effective in enhancing the model's accuracy and robustness.

**Results**

The results of this study are compelling, demonstrating the effectiveness of the proposed modifications:

1. **Dataset Comparison:** The comparison between training with the VEDAI and VAID datasets reveals superior performance when utilizing the VAID dataset for vehicle detection and classification. This finding underscores the importance of a well-annotated and diverse dataset in training effective deep learning models.
2. **Testing Scenarios:** Evaluation across different testing scenarios, labeled as Scenes A-D, highlights the robustness of the proposed method under various road and traffic conditions. The modified Faster R-CNN architecture shows a consistent improvement in performance across these diverse scenarios.
3. **Performance Metrics:** The adoption of the ReLU activation function within the modified Faster R-CNN architecture results in a notable improvement in mean Average Precision (mAP). This improvement is particularly significant when compared to the original framework, demonstrating the benefit of optimizing activation functions for specific tasks.

**Strengths and Weaknesses**

The study presents several strengths that contribute to its overall impact:

1. **Framework Adoption**: The use of a modified Faster R-CNN framework with ResNet101 for feature extraction has shown improved performance over standard architectures. This adoption is crucial in achieving high accuracy in vehicle detection and classification.
2. **Comprehensive Analysis:** The detailed analysis and comparison with existing datasets, such as VEDAI, demonstrate the effectiveness of the proposed method under various road and traffic conditions. This comprehensive approach ensures that the method is robust and applicable to real-world scenarios.
3. **Optimization Techniques:** The experimentation with different activation functions, such as softplus, ELU, and ReLU, illustrates a thorough approach to optimizing model performance. This experimentation is a key strength in fine-tuning the model for maximum accuracy.

However, the study also identifies certain weaknesses:

1. **Model Generalization:** The study could benefit from a more extensive analysis of the model's generalization to challenging scenarios beyond the tested conditions. A broader range of scenarios would provide a more comprehensive assessment of the model's robustness.
2. **Dataset Imbalance:** 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. Addressing this imbalance is crucial for developing a more universally applicable model.
3. **Qualitative Analysis:** The project evaluation could be enhanced by including qualitative analysis and visual demonstrations of detected vehicle instances in challenging scenarios. These visual demonstrations would provide a clearer understanding of the model's practical performance.

The study by Yaw Okyere, Adu-Gyamfi, Sampson Kwasi Asare, Anuj Sharma, and Tienaah Titus titled "Automated Vehicle Recognition with Deep Convolutional Neural Networks" explores this avenue by developing a system to classify vehicles based on the Federal Highway Administration's (FHWA) 13 vehicle types. The system leverages video data from CCTV cameras to achieve high accuracy in vehicle recognition under various real-world conditions.

This research makes several significant contributions to the field of automated vehicle recognition:

1. **Advanced Technology Utilization:** By leveraging DCNNs, the study enhances feature learning and classification capabilities, outperforming traditional machine vision techniques. This advanced technology enables the model to learn complex features from vehicle images, improving classification accuracy.
2. **High Precision Rates:** The system achieves precision rates ranging from 82% to 100% across different vehicle classes. This high level of accuracy demonstrates the effectiveness of DCNNs in vehicle recognition tasks, even under challenging conditions such as varying traffic volumes, lighting, and video resolutions.
3. **Robustness:** The robustness of the system is evident in its ability to handle varying traffic and lighting conditions, showcasing its practical utility in real-world applications. This robustness ensures reliable performance across different scenarios, making it suitable for deployment in diverse environments.

**Methodology**

The methodology adopted in this study is comprehensive and detailed:

1. **Region Proposal Generation:** The study utilizes Selective Search to generate region proposals. This technique helps in identifying potential areas in the images that may contain vehicles, thereby narrowing down the search space for the DCNN.
2. **Feature Extraction:** DCNNs are employed to extract feature descriptors from the proposed regions. This step involves using pre-trained models on large datasets (e.g., ILSVRC2012) followed by domain-specific fine-tuning on CCTV data. The use of pre-trained models accelerates the training process and enhances feature extraction capabilities.
3. **Classification:** Linear Support Vector Machines (SVMs) are implemented to classify vehicle types based on the extracted features. The combination of DCNNs for feature extraction and SVMs for classification leverages the strengths of both techniques, resulting in high classification accuracy.
4. **Performance Evaluation:** The system's performance is evaluated under various conditions, including different traffic volumes, lighting scenarios, and video resolutions. This thorough evaluation ensures that the model is tested comprehensively, providing insights into its robustness and reliability.

**Results**

The results of this study are impressive and highlight the effectiveness of the proposed system:

1. **Precision Rates:** The system achieves average precision rates ranging from 82% to 100% across different vehicle classes. Notably, the model excels in recognizing motorcycles and buses, achieving 100% precision for these classes. However, it faces challenges in distinguishing between van and pickup variants, with a precision rate of 82%.
2. **Evaluation Conditions:** The system performs best under free-flow daytime conditions with good video quality. This finding indicates that optimal conditions enhance the model's accuracy, although it remains robust under less favorable conditions as well.
3. **Challenges:** The study identifies several challenges, including lower precision rates for certain vehicle classes (e.g., vans and pickups) due to limited training data. Additionally, occlusions by larger vehicles impact recall rates, particularly for passenger cars. These challenges highlight areas for further improvement and optimization.

**Strengths and Weaknesses**

The study exhibits several strengths:

1. **Advanced Technology:** Leveraging DCNNs allows for robust feature learning and classification, surpassing traditional machine vision techniques. This technological advancement is a significant strength of the study.
2. **Accurate Classification:** Achieving precision rates of 82% to 100% for different vehicle classes demonstrates the effectiveness of the approach. This accuracy is critical for practical applications, where high precision is essential.
3. **Robustness:** The system's ability to handle challenging conditions like varying traffic and lighting conditions showcases its practical utility. This robustness is crucial for real-world deployments, where conditions are often unpredictable.

However, the study also identifies some weaknesses:

1. **Lower Precision for Certain Classes:** Some vehicle classes, such as vans and pickups, have lower precision rates due to limited training data. This issue affects the system's overall performance and highlights the need for more comprehensive datasets.
2. **Sensitivity to Occlusions:** Occlusions by larger vehicles impact the system's recall rates, especially for passenger cars. Addressing this sensitivity is important for improving the model's reliability.
3. **Computational Complexity:** DCNNs are computationally expensive, requiring substantial processing power and time for model training and inference. This complexity can be a barrier to real-time applications and widespread adoption.

The application of Convolutional Neural Networks (CNNs) in vehicle recognition tasks has shown significant promise in enhancing the accuracy and efficiency of classification systems. The study by W. Maungmai and C. Nuthong, titled "Vehicle Classification with Deep Learning," delves into the use of CNNs to address the challenges associated with vehicle classification within surveillance videos. This research focuses on two primary classification tasks: vehicle type and vehicle color. The objective is to leverage CNNs to improve the accuracy of these classifications compared to traditional methods.

**Key Contributions**

This research makes several noteworthy contributions to the field of vehicle classification:

1. **Cutting-edge Technology Utilization:** The paper demonstrates the application of CNNs for vehicle classification tasks, highlighting the advantages of deep learning techniques in real-world applications. By comparing CNN-based methods with traditional approaches like decision trees, random forests, and densely connected neural networks (DNNs), the study showcases the improvements in classification accuracy that can be achieved with CNNs.
2. **Comprehensive Experimental Setup:** The study provides a detailed description of its experimental setup, including dataset characteristics, model architectures, and hyperparameters. This transparency allows for reproducibility and offers valuable insights into the specific configurations that contribute to the model's performance.

**Methodology**

The methodology adopted in this study is methodical and well-documented:

1. **CNN Architecture:** The proposed CNN architecture consists of two convolutional layers followed by pooling layers and fully connected layers. This architecture is designed to extract and learn hierarchical features from the vehicle images, which are crucial for accurate classification.
2. **Dataset Utilization:** The study employs a specific dataset of extracted vehicle images for training and testing the CNN models. This dataset includes various vehicle types and colors, providing a diverse set of samples for robust model training.
3. **Performance Evaluation:** The model's performance is evaluated using metrics such as accuracy for both vehicle type and color classification. This evaluation allows for a clear comparison with existing methods and highlights the areas where the CNN approach excels or requires further refinement.

**Results**

The results of this study are significant and highlight the efficacy of the proposed CNN approach:

1. **Vehicle Type Classification:** The CNN-based method achieves an accuracy of 84.65% in vehicle type classification. This performance is superior to existing methods like decision trees and random forests, demonstrating the effectiveness of CNNs in this task.
2. **Vehicle Color Classification:** For vehicle color classification, the model achieves an accuracy of 70.09%. While this is a notable achievement, the study identifies opportunities for improvement through further refinement of CNN hyperparameters and model structures.

**Strengths and Weaknesses**

The study exhibits several strengths:

1. **Advanced Technology:** Leveraging CNNs for vehicle classification tasks demonstrates the cutting-edge use of deep learning in real-world applications. This technological advancement is a significant strength of the study.
2. **Improved Accuracy:** The paper shows that the proposed CNN-based method improves accuracy compared to traditional techniques like decision trees, random forests, and densely connected neural networks. This improvement is crucial for practical applications where high accuracy is essential.
3. **Comprehensive Setup:** The study provides a comprehensive experimental setup, including dataset characteristics, model architectures, and hyperparameters. This thorough documentation enhances the reproducibility and reliability of the research findings.

However, the study also identifies some weaknesses:

1. **Performance Variability:** The results indicate some variability and instability in performance metrics (e.g., standard deviations), suggesting the need for further optimization of CNN hyperparameters. This variability can impact the reliability of the model in different scenarios.
2. **Limited Real-world Discussion:** Although the proposed CNN approach shows promising results, the paper could benefit from discussing specific challenges faced in real-world scenarios, such as occlusions and varying lighting conditions. Addressing these challenges is crucial for improving the model's robustness and applicability in diverse environments.

**Methodologies and Techniques for Your Project**

**Step 1: Vehicle Classification**

**Dataset Collection:**

* **Collect a Dataset:** Gather a diverse dataset of vehicle images from sources like Kaggle, academic datasets, or web scraping tools.

**Model Training:**

* **Preprocessing:** Resize and preprocess the images for consistency.
* **Model Selection:** Choose CNN architectures like VGG, ResNet, or EfficientNet.
* **Transfer Learning:** Utilize pretrained models on ImageNet for feature extraction and fine-tune on the vehicle dataset.

**Implementation in Jupyter Notebook:**

* Use Python libraries like TensorFlow/Keras or PyTorch for model development.
* Leverage Jupyter Notebook for step-by-step implementation and experimentation.

**Related Projects and Articles:**

* **Kaggle Datasets:** Utilize specific vehicle classification datasets.
* **Research Papers:** Refer to academic papers on image classification and vehicle recognition.

**Step 2: Vehicle Recognition (Object Detection)**

**Dataset Preparation:**

* **Annotate Data:** Label images with vehicle bounding boxes and attributes like model, color, size, and number plate.

**Model Training:**

* **Object Detection Models:** Implement models like YOLO, Faster R-CNN, SSD.
* **Multi-task Learning:** Jointly predict vehicle attributes and number plate recognition.

**Deployment and Inference:**

* Deploy trained models for inference on local or cloud platforms like AWS or Google Cloud.

**Related Projects and Articles:**

* **GitHub Repositories:** Search for open-source projects on vehicle recognition.
* **Research Papers:** Look for studies on vehicle attribute recognition and number plate detection.

**Additional Considerations:**

* **Data Augmentation:** Apply techniques to increase dataset diversity and improve model robustness.
* **Evaluation Metrics:** Use metrics like mAP for object detection to assess performance.
* **Ethical Considerations:** Ensure compliance with privacy regulations when working with number plate data.

**Evaluation and Effectiveness Studies**

Research indicates that CNNs and DCNNs significantly improve vehicle classification and recognition accuracy. However, challenges such as dataset imbalance, occlusions, and variability in real-world conditions need addressing. The effectiveness studies demonstrate that leveraging advanced neural network architectures and transfer learning can enhance model performance. Furthermore, detailed annotations and diverse datasets are crucial for robust vehicle recognition systems.

**Conclusion**

This project involves a combination of image classification and object detection tasks to classify and recognize vehicles in images. By leveraging available datasets, pretrained models, and open-source implementations, a robust vehicle recognition system can be built and deployed using Jupyter Notebook. Continuously exploring related projects and research articles will enhance understanding and implementation skills. This literature review highlights the advancements in vehicle classification and recognition, providing a solid foundation for developing a sophisticated and effective system.