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CNN and YOLOV8m Based Car Classification

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Abstract

Vehicle identification based on tail lights involves recognizing vehicles by the unique design and pattern of their tail lights. This method uses distinct visual features to identify specific models. To identifying vehicles by detecting their tail lights. Tail lights signal a vehicle's presence and actions, especially at night or in poor visibility. By using innovative image processing techniques like the HAAR transformation and dee learning, this study aims to accurately identify vehicles based on the head and tail light patterns. This system detects tail lights in real-time, providing important data for autonomous driving, traffic monitoring, and collision avoidance. The effectiveness of Haar Cascade Classifiers and deep learning technique, such as Convolutional Neural Networks (CNNs), is evaluated to improve identification accuracy and speed. As self-sufficient vehicles become more common, reliable tail light detection is important for road safety. By training models on diverse tail light images, the system can identify vehicle make and model build on tail light design in various lighting conditions and angles. Tail lights, important for both function and style, often feature unique shapes and LED arrangements that help in identification. These designs can be characterized by their geometric patterns (like circles, rectangles, or more complex shapes), the distribution and intensity of light.

Keywords: *vehicle, head and Tail light, recognition, Image Processing*

1. Introduction

Vehicle identification based on vehicle tail lights involves using the unique patterns and characteristics of tail lights to identify and distinguish different vehicles. Tail lights typically consist of specific arrangements of LEDs or bulbs, encased within a housing designed to emit light in a particular pattern. By analyzing the arrangement, shape, color, and intensity of light emitted by the tail lights, along with any unique features such as branding logos or specific designs, vehicles can be identified or differentiated from one another. This identification method can be used for various purposes, including law enforcement, traffic management, and security systems. Vehicle identification plays a significant role in various domains, including law enforcement, traffic management, and toll collection. Traditional methods of vehicle identification rely on license plate recognition, but advancements in technology have led to the exploration of alternative identification methods, such as vehicle tail light-based identification. This approach leverages the unique characteristics of a vehicle's tail lights to accurately identify and differentiate vehicles. Vehicle identification based on vehicle tail lights is a technique used to recognize and classify vehicles based on the unique patterns and designs of their rear lights. Tail lights vary in color, shape, size, and arrangement, often following manufacturer specific designs. This method leverages these differences to identify the make and model of a vehicle, providing a means of classification without relying on other identifying features like license plates. Advanced computer vision algorithms and machine learning models can be trained to detect these distinct tail light patterns from images or videos, enabling purposes suchas traffic monitoring, surveillance, and automated parking systems. Identifying vehicles by tail lights can be particularly useful in low-light conditions or from rear-facing camera perspectives, where other distinguishing features may be harder to design.

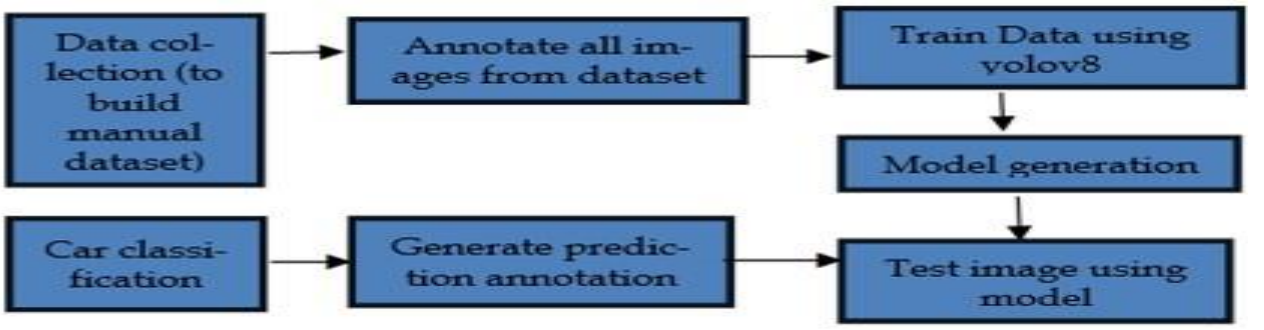

Fig1, Block Diagram

2. Related work / Literature Survey

Sebastien Razakarivony et al., [1] focuses on introduced a benchmark database for vehicle detection in aerial imagery, designed to challenge automatic target recognition systems with small vehicles exhibiting various angles, lighting conditions, colors, and sizes. The database ensures consistency in experiments, enabling researchers to rigorously test and compare their algorithms. By setting a standard for evaluation, this work aims to advance vehicle detection in aerial images and foster innovation in the field.

Chinmoy Jyoti Das et al., [2] was focuses on recognizing vehicles at night, a challenge due to poor visibility. This work addresses the challenge of nighttime vehicle recognition due to poor visibility. It emphasizes detecting tail lights, complicated by low light and reflections. The proposed system enhances vehicle recognition in low-light conditions, potentially improving road safety and traffic management at night.

Kuan-Hui Lee at el.,[3] explores an Vehicle taillight recognition is crucial for automated driving, enhancing prediction of other vehicles actions and optimizing the ego vehicle's path. Modern approaches use Convolutional Neural Networks (CNNs) and Long Short-term Memory (LSTM) networks, with attention mechanisms focusing on critical features. To approach, combining CNNs, LSTMs, and attention models, achieves high precision on the UC Merced Vehicle Rear Signal Dataset, proving its effectiveness.

Ming Liu et al., [4] proposed on developed a real-time framework for vehicle taillight recognition, addressing speed and accuracy challenges of existing methods. Their approach includes detection and recognition stages, improving accuracy with a Finer Detection Block and dense anchor regression. They introduced a Siamese CNN-GRU network to capture short-term and long-term features, achieving 94.34% mean recall at 103 frames per second on an NVIDIA GeForce GTX 1080Ti GPU.

Shahnaj Parvin et al., [5] Identifying vehicles at night is important for improving road safety, as many accidents happen due to poor lighting. created a vision-based system for nighttime vehicle recognition and tracking using taillight and headlight features. It achieves 97.22% accuracy with centroid tracking and the Euclidean Distance method, processing frames in 0.01 seconds and identifying both double and single lights, including from motorcycles, improving road safety.

Dr. Shailesh V. Kulkarni et al., [6] focuses on the HAAR Cascade approach for car identification and brake light detection, crucial for enhancing visibility and signaling in autonomous vehicles. Their research focuses on detecting brake lights ahead to prevent collisions and maintain safe distances. They employ Haar Cascade transformation and deep learning techniques in Python for accurate and fast detection, addressing the increasing need for reliable systems as autonomous vehicles become more widespread.

Priyanka Ankireddy et al., [7] focuses on using the YOLOv8 (You Only Look Once version 8) deep learning technique to enhance image processing quality for vehicle detection and tracking. used YOLOv8 for high-quality vehicle detection and tracking, aiming to automate car identification in images and videos for enhanced traffic surveillance and safety. They integrated neural networks and improved Deep SORT with focus loss to achieve a 98.48% success rate in recognizing cars after training on public datasets, advancing automated techniques in traffic monitoring systems.

Gajula Mounika et al**.,** [8] introduces a deep learning model using YOLOv5 to detect and recognize vehicle taillights in real-time. This model, crucial for low-light conditions and accident prevention, achieved 92.36% accuracy after 50 training iterations. The research highlights YOLOv5's potential to enhance autonomous driving safety and reliability through accurate real-time taillight detection.

Geesung Oh et al., [9] proposed an idea of Light detection have been advancements in advanced driver assistance systems (ADAS) and autonomous driving. proposed using YOLOv8 for one-stage brake light status detection, essential for ADAS and autonomous driving. Their method enhances safety by swiftly detecting vehicles and monitoring brake lights in real-time, facilitated by efficient processing on edge devices through transfer learning on a custom dataset. This method improves safety and understanding in ADAS and autonomous driving.

Huayue Zhang et al., [10] proposed a method to improve front-vehicle taillight recognition. The paper enhances taillight detection by combining image processing with object detection techniques. Using HSV color space and corrosion expansion algorithms, they upgraded the YOLOv8s model with a P2 small target detection module and Coordinate Attention mechanism. Addressing sample imbalance with the EIOU Loss function, they achieved a 9.3% improvement in mean Average Precision (mAP), significantly boosting detection accuracy and robustness.

Paper	Objective	Technique Used	Dataset	Accuracy
[1]	A new database of aerial images is available to test vehicle detection algorithms in varied environments.	Target Recognition Algorithm	3700 annotated targets and 1200 images	Best Accuracy with 85%.
[2]	Authors proposed this project to detect a vehicle number using taillight which helps to identify the vehicles at night time	Image Processing segmentation technique	Dataset is taken from Kaggle where training 536 images and validation 90 images.	The project Accuracy was of 86%
[3]	Optimize the ego vehicle's path and predict other vehicles' actions using taillight recognition for automated driving.	CNNs, LSTMs, Attention Mechanisms	UC Merced Vehicle Rear Signal Dataset	High accuracy
[4]	Author design a light-weight framework for vehicle taillight recognition in real-time.	ResNet(Recurrent Neural Network)	Testing Images=500 Training 3000	The best Accuracy was of 94.34 %
[5]	nighttime vehicle detection and tracking system using taillight and headlight features to	Computer vision/Image Processing Techniques	Dataset used of two types NiTra and NVDD Images=2779 for	It had a high accuracy of 97.22 %

	enhance safety and prevent accidents.		testing and 6756 frames for test set	
[6]	The study was about vehicle identification based on back light and front face.	Haar-cascade algorithm. (Haar)	Images with different pixels and intensities is used.	It is of high accuracy with 94%
[7]	Aim is to ability to recognize and track cars in a Traffic surveillance	DeepSORT Algorithm, YOLO v8	BDD100k picture dataset.	The accuracy was grown to 98.48 %
[8]	Automated cars represent a technological leap in the automobile industry, often detecting vehicles ahead by their taillights in low-light conditions.	YOLO /Deep Learning/CNN	Dataset contains 4032 images Testing contains 20% and for training 80%.	The accuracy was of 92.36 %
[9]	The aim is to recognize to recognize the ADAS and autonomous driving technologies.	YOLO v8	Dataset contains 11,000 images Test Dataset=0.79%	It has a high Accuracy
[10]	Aim is to predicting the intention of vehicle ahead with taillight matching	YOLO v8s Model	Taillight dataset is of 80% and 20%data is of actual road condition	The model accuracy is of 9.3%

Table 2.1 Comparison table

3. Proposed Methodology

Vehicle identification via tail lights starts by captures process by rear-end images with cameras, focusing on enhancing clarity and isolating the tail light area. Features such as shape, color, and light distribution are extracted and analyzed. Convolutional Neural Networks (CNNs) are then trained on large datasets to classify vehicle makes and models based on these features. The system compares these features with a database for real-time identification, beneficial for security, traffic management, and law enforcement, despite challenges like varying tail light designs and environmental conditions. To initiate the process, a dataset containing annotated pictures with labeled bounding boxes around objects of interest is essential. These annotations specify the object class and coordinates needed for training algorithms like YOLO.

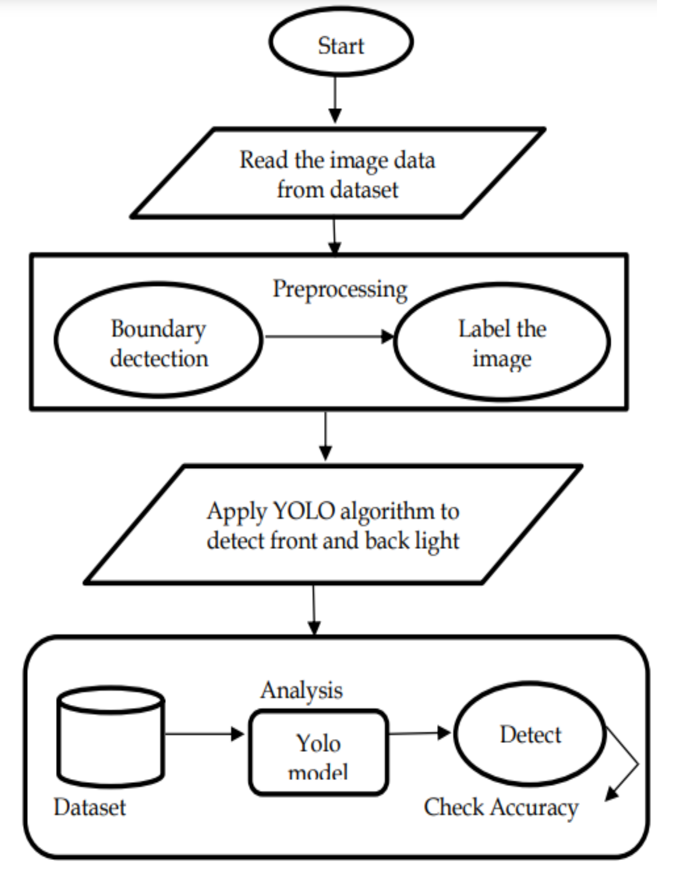

Fig 3.1 Flow diagram

1) Read the image from dataset:

- The dataset is iterated in batches for training or evaluation, and datasets are split into training, validation, and test sets to assess and improve model performance.

- The accuracy model is tested on manual dataset.

2) Data Preprocessing:

Data is preprocessed by clean and preprocess the images, includes resizing, normalization, augmentation.

Data Cleaning:-

- **Remove Duplicates:** Verify the dataset is free from duplicate images.
- **Quality Check:** Eliminate images that are blurry, overexposed, or underexposed.

Data Annotation

- **Bounding Boxes:** Utilize tools like LabelImg to draw bounding boxes around tail lights.
- **Segmentation Masks:** For greater precision, create segmentation masks that outline the exact shape of the tail lights.

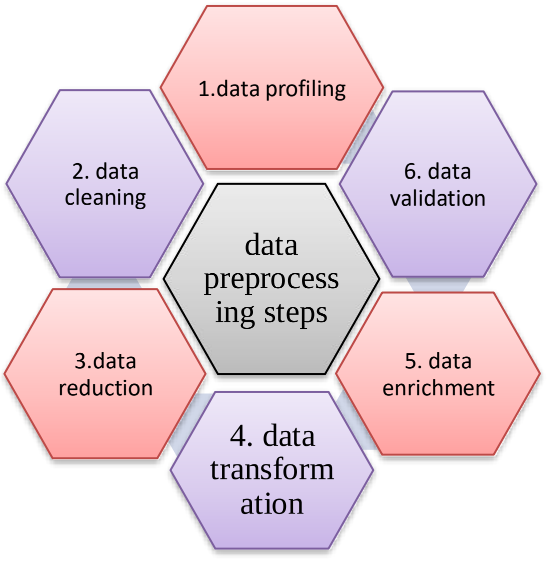

Fig 3.2 Data Preprocessing steps

3) Yolo algorithm predicts:-

The YOLO (You Only Look Once) algorithm, renowned for its speed and precision in object detection, provides several key predictions:

- **Bounding Boxes:** YOLO predicts bounding boxes that enclose objects within an image. These boxes define the object's location using coordinates for the top-left corner and dimensions of width and height.

- **Class Labels:** Each predicted bounding box is associated with a class label that identifies the type of object detected, such as "car," indicating what the object is.

- **Confidence Scores:** YOLO assigns confidence scores to each predicted bounding box, indicating the algorithm's certainty that the box accurately contains an object of any class. These scores are crucial for assessing the detection accuracy created on the model's training data.

YOLOV8m Algorithm Steps:-

Step 1- Input Processing: Accepts an input image or video frame containing vehicles with visible tail lights.

Step 2- Feature Extraction: Utilizes YOLOv8m's Convolutional neural network (CNN) to extract distinctive features from the input image.

Step 3- Tail Light Detection: Utilizes YOLOv8m's object detection capabilities to accurately locate and identify tail lights within the image.

Step 4- Vehicle Classification: Determines the vehicle's make or model depend on the identified tail lights using additional classification layers.

Step 5- Output: Generates the final result displaying bounding boxes around detected tail lights and corresponding vehicle classifications.

Step 6- Post-Processing: Optionally improves detection accuracy by refining or filtering results based on confidence scores or specific criteria.

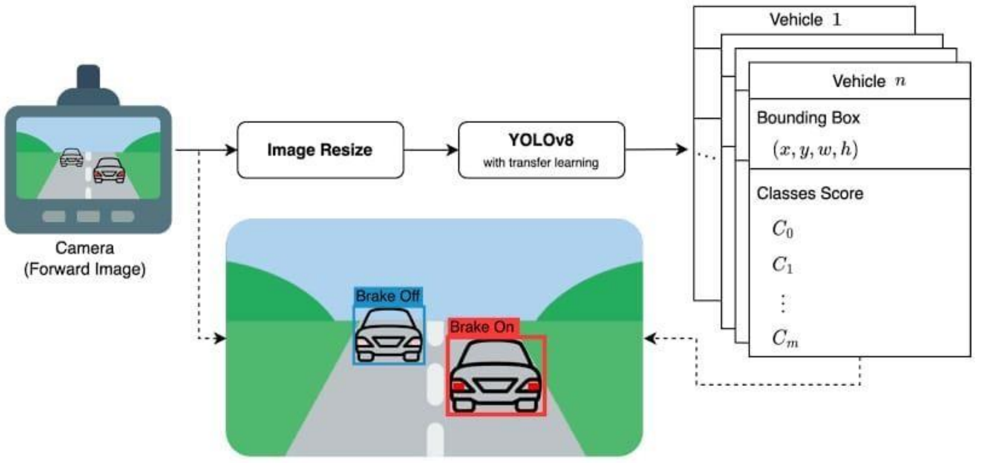

Fig 3.3 Yolo Works

In fig 3.3 vehicle forward image (tail light on or off) with resize the image is the act of altering the size dimensions of a digital image with yolov8(you only look once version 8) with transfer image and bound boxes with classes and annotation (x-axis, y-axis, width, height).

4. Experimental results and Discussion

Car identification based on tail light patterns is a promising field in computer vision, utilizing CNNs and YOLOv8 for high accuracy. Recent studies have shown over 90% accuracy in identifying vehicle make and model using these advanced models. This technology is valuable for tracking tail vehicles, monitoring traffic violations, and enhancing autonomous driving safety. However, challenges such as varying lighting, occlusions, and low-resolution images, along with the need for an updated database of tail light patterns, remain. Despite these challenges, ongoing advancements in machine learning and image processing are predictable to enhance this technology, making it increasingly valuable for future applications.

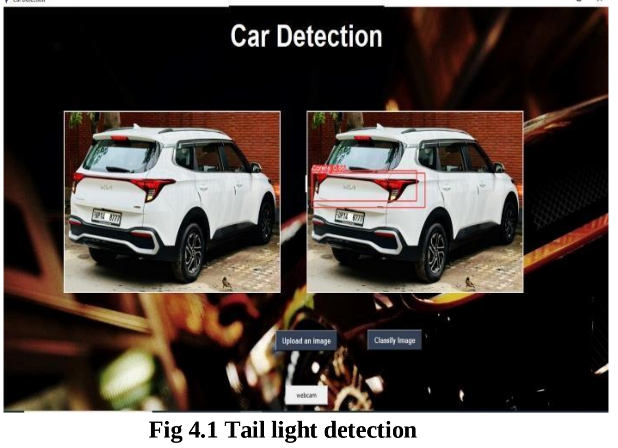

Fig 4.1 Tail light detection

Fig 4.2 Tail light detection

Analysis of graph

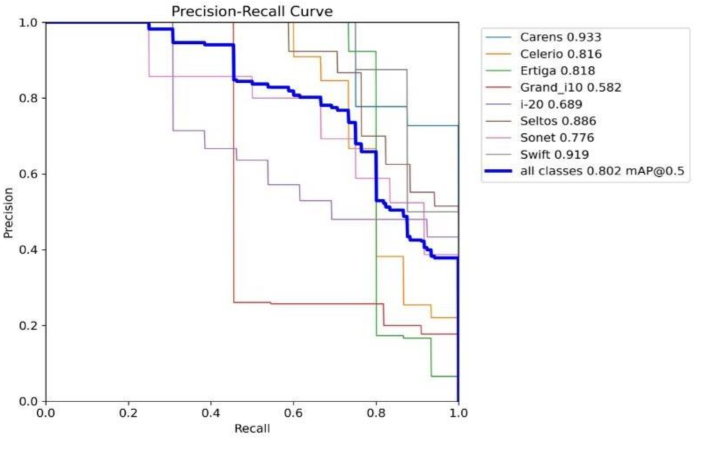

Fig 4.3 precision-recall curve

In Fig 4.3 The precision-recall curve give 85% accuracy. Graph plots precision values on the x-axis and recall values on the y-axis across various classification thresholds. This curve visually represents how the balance between precision and recall changes with different threshold settings, showing how well the model identifies positive instances (recall) and how accurate those identifications are (precision).

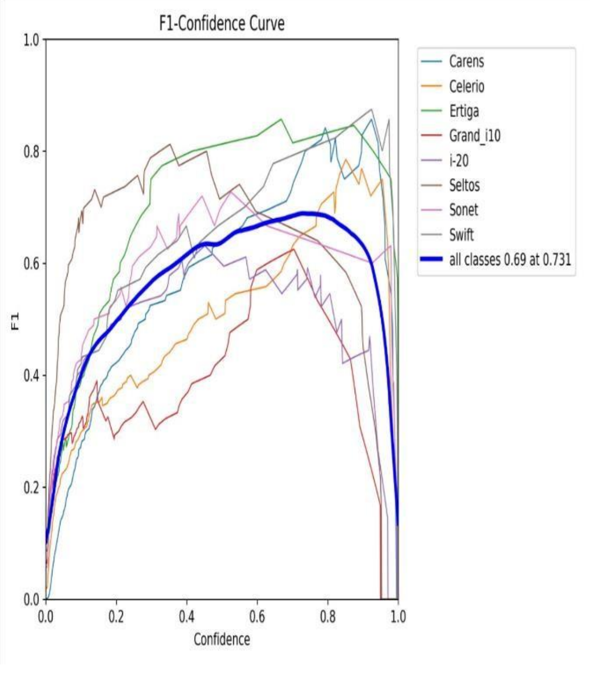

Fig 4.4 F1-confidence curve

In Fig 4.4 represents statistic for evaluating a model's accuracy that combines recall and precision is called the F1 score. When there are unequal class distributions, it is particularly helpful for striking a balance between these two factors. The following formula is used to determine the F1 score:

$$\text{F1 score} = 2.\frac{\text{Precision.Recall}}{\text{Precision+Recall}} \longrightarrow \textbf{eq (1)}$$

Precision is defined as the proportion of accurate positive forecasts to all positive forecasts. (ratio of true positive predictions to the total positive predictions). The proportion of actual positive instances to true positive predictions. Recall is defined as the ratio of true positive predictions to the total actual positives. The probability score that the model assigns to a certain prediction which expresses the model's level of certainty on its accuracy (82%) is referred to as confidence.

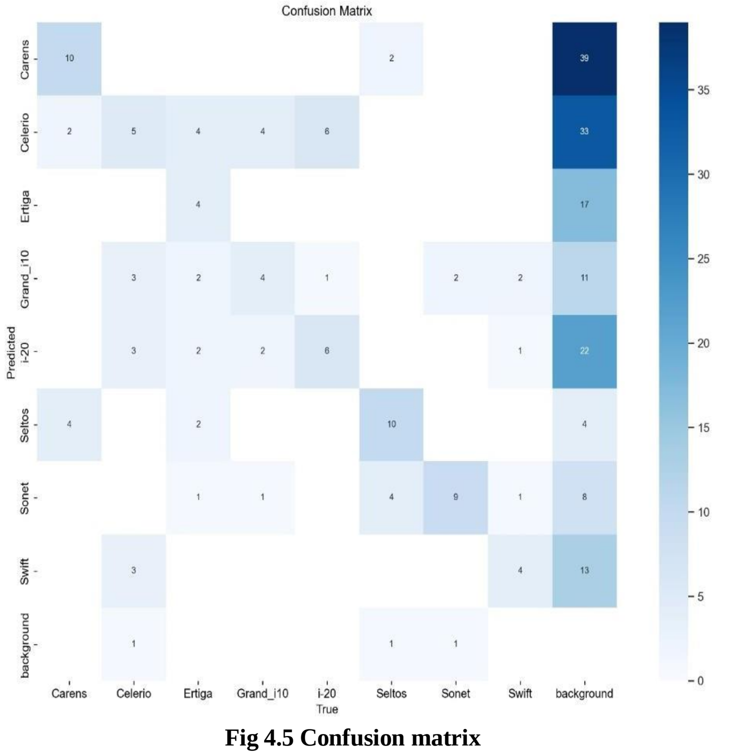

Fig 4.5 Confusion matrix

In Fig 4.5 represents the value of metrics/ precision and metrics/recall with respect to data taken to produce the graph. A cost matrix is typically a square matrix. A cost matrix, or cost-sensitive matrix, is used in machine learning to assign different costs to various prediction errors. This is useful when the consequences of errors differ greatly. Here's an explanation of a cost matrix with the x-axis and y-axis where:

- **Rows (Y-axis)** is represent the actual classes (true labels).
- **Columns (X-axis)** is represent the predicted classes (predictions made by the model).

A cost matrix in car identification based on vehicle taillight recognition assigns different costs to various prediction errors. This helps optimize the model for real-world scenarios where certain errors may be more costly than others.

Conclusion

Vehicle identification through tail lights is essential in various contexts, including law enforcement, accident investigations, and vehicle tracking. Tail lights not only fulfill critical safety functions but also display distinct identifiers like vehicle model details, brand logos, and compliance marks. These identifiers are important for promptly determining the vehicle's make and model, which is vital in identifying vehicles involved in hit-and-runs, traffic violations, or situations where visual identification is challenging. Moreover, advancements in technology such as high resolution imaging and automated recognition systems improve the accuracy and efficiency of identifying vehicles based on their tail lights, thereby improving investigative processes and ensuring public safety.

References

1. Sébastien Razakarivony, Frédéric Jurie, "*Vehicle Detection in Aerial Imagery : A small target detection benchmark*", 4 Mar 2015, pp.31-42.

2. Chinmoy Jyoti Das, Parismita Sarma, "*Vehicle Recognition Based on Tail Light De- tection*", I nternational Journal of Advanced Re- search in ComputerandCommunicationEngi-neering,Vol.5,pp.527-529,2016,DOI 0.17148/IJARCCE.2016.53129

3. Kuan-Hui Lee, Takaaki Tagawa, Jia-En M. Pan, Adrien Gaidon, Bertrand Douillard, *" An Attention-based Recurrent Convolutional Net- work for Vehicle Taillight Recognition"*, pages2365-2370,9 june 2019,pp.1-6, DOI 10.1109/IVS.2019.8813911

4. Ming Liu, Bingyan Liao, Chenye Wang, Yayun Wang and Yaonong Wang, *"Real-Time Vehicle Taillight Recognition Based on Siamese Recurrent Neural Network"*, IOP Publishing Journal of Physics: ConferenceSeries,2020,pp.1-8. Shahnaj Parvin, Liton Jude,

5. Shahnaj Parvin, Lion Jude *"Vision based On Road Nighttime Vehicle Detection and Tracking Using Taillight and Headlight Features",* Journal of Computer and Communications, March 9, 2011. 53(9).

6. Dr. Shailesh V, Dr Praveen G Gawande, Dr. Anup W Ingle *CAR IDENTIFICATION FOR BRAKE LIGHT DETECTION USING HAAR CAS- CADE APPROACH*",2023,pp.20-30

7. Priyanka Ankireddy et al., "Vehicle Detec-tion and Tracking Using YOLOv8 and DeepLearning to Boost Image Processing Quality", IJFANS INTERNATIONAL JOURNAL OFFOOD AND NUTRITIONAL SCIENCES,Volume 11, Issu 11, 2022, pp.3722-3735.

8. Gajula Mounika, Vasundra S, "Deep Learn- ing Model for Vehicle Taillight Detection and Recognization in Autonomous Driving", Vol- ume 21, Page 179-184, January 2023, Doi: 10.48047/NQ.2023.21.3.NQ33020

9. Geesung Oh, Sejoon Lim, "One-Stage Brake Light Status Detection Based on YOLOv8", 25 August 2023, vol.23,pp.1-18, **https://doi.org/10.3390/s23177436**

10. Huayue Zhang, Junyou Zhang, ShufengWang, "Research on Front-Vehicle taillightrecognition based on image processing andmatching",pp.1-15,2024,