Missing Substance Detection

Abstract

Vehicle theft is a rising crime across the globe. The fact that GPS trackers are not a standard fit in all vehicles and the vehicles lack internet connectivity makes tracking down stolen vehicles a challenge for officials. GPS signals can be affected by different environmental factors such as mountains, or dense foliage, which can cause inaccuracies in location tracking. To overcome these issues, the proposed solution utilizes the CCTV network to track the path taken by a stolen vehicle and accelerate the search process. The proposed idea introduces an effective solution for identifying and tracking stolen vehicles using CCTV footage, employing modern computer vision and deep learning techniques. Scrutinising the CCTV footage from different sources can speed up the response and enhance recovery efforts while maintaining data privacy. This paper suggests a tracking solution using the existing CCTV infrastructure without any additional hardware to be fitted in the vehicles.

Keywords: Vehicle tracking, Computer vision, Deep learning.

1. Introduction

Vehicle theft is a persistent challenge for law enforcement agencies globally, necessitating innovative approaches to effectively combat this crime. Vehicle theft in India is a rising concern in major cities like New Delhi. Vehicle theft has increased 2.5 times in 2023 as compared to 2022 [1]. Traditionally, law enforcement personnel rely on fieldwork to gather information from various sources such as eyewitness sightings or tips from nearby individuals and businesses. However, this method is often labour-intensive, time-consuming, and prone to inaccuracies. India Survey statistics with citation about the theft to be included here.

In recent years, advancements in technology have led to the adoption of more sophisticated techniques to address vehicle theft. One such approach involves leveraging surveillance cameras deployed in public spaces. These cameras continuously capture vast amounts of visual data, providing valuable insights into criminal activities, including vehicle theft.

However, analyzing this data manually is a daunting task due to its sheer volume and complexity. To overcome this challenge, law enforcement agencies are turning to smart techniques powered by artificial intelligence (AI) and computer vision.

One modern technique involves employing AI algorithms to analyze CCTV footage and automatically detect, identify, and track vehicles. These algorithms can recognize license plates, vehicle make and model, and even unique characteristics such as dents or decals. By processing footage from multiple cameras, authorities can create a comprehensive route map of the stolen vehicle's movements, significantly enhancing their ability to apprehend suspects and recover stolen vehicles.

Moreover, AI-powered systems can analyze patterns and anomalies in vehicle behaviour, helping law enforcement agencies predict and prevent future thefts. For example, if a vehicle deviates from its usual route or exhibits suspicious behaviour, such as frequent stops in secluded areas, the system can automatically alert authorities, enabling them to intervene swiftly.

By integrating smart technology with existing surveillance infrastructure, law enforcement agencies can streamline the process of investigating vehicle thefts, reduce reliance on manual labour, and improve overall effectiveness. These advancements not only enhance law enforcement capabilities but also serve as a deterrent to potential offenders, contributing to a safer and more secure society.

The structure of the paper is as follows. Section 2 describes the literature survey performed related to the problem statement. Section 3 describes the proposed system with block diagrams and their detailed description. Section 4 explains the methodology employed. Section 5 discusses the implementation details, and Section 6 covers the results. Finally, the paper concludes in section 7 followed by section 8 being the references.

2. Literature Survey

K.V. Kadambari, et.al [2], put forth a system which uses Deep Learning technique to extract number plates from the cars using CCTV footage captured in Arunachal Pradesh. Author employed Tesseract OCR to recognize the characters from the number plates.They effectively addressed error handling by adhering to the standard number plate template. In cases where a number is predicted instead of a character, the system intelligently predicts the character that is most likely to be present, and vice versa.
However a limitation of the proposed system is the inability to handle skewed number plates. Despite having multiple iterations the system struggles to get an accurate straightened image.

Xiying Li et.al [3], aims to quickly search, locate and track the target car using CCTV cameras. Licence plates cannot be identified in every case it could be due to occlusion, bad light or some glaze, hence author plans to focus on feature extraction on the cars captured in the video. To extract features and compare them with the candidate car, they employ the VGG16 model and use Triplet loss and joint multiple loss functions as loss function. The limitation of VGG16 compared to EfficientNet is that it achieves higher accuracy with significantly fewer parameters, enabling more efficient model deployment on resource-constrained devices. EfficientNet has a balanced design which provides a superior trade-off between computational efficiency and accuracy.

Anil Sharma, et.al [4], 2020.tanmay.thakare@ves.ac.in adopted a state-representation learning using reinforcement learning-based policy to automate the camera selection process. In comparison with other methods, their strategy produces high-quality results as it employs learned state representations, which helps decrease the time spent on training the Reinforcement Learning policy. They also implemented a reward function into semi-supervised policy training. However, they did not provide the relation between the size of the network and the time required to find the next camera.

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Delong Cai (2023)[7], introduced the Corner Point Foreground Area Intersection over Union loss function as a new means of enhancing bounding box regression, especially for better localization of small objects. This new loss function overcomes problems associated with the overlap of boxes because it includes multiple objects, which either partially or completely have an overlapping rate higher than 70%, and therefore distinguishing between these two becomes problematic. This method was tested on datasets including vizDrone-DET2019 and SODA-D using both anchor YOLOv5 as well as the non-anchor youlo8. As such, the CFIoU loss function can be considered a major development in improving the bounding box regression accuracy principle, particularly for situations with small-scale object localisation and high overlap.

Shailendra Shende et al. (2023)[8], proposed a CNN-based approach towards missing object detection. This approach uses CNNs that detect missing objects embedded within images. During Image Classification, the model was trained using a dataset of 500 images. Even with the insufficient training dataset, the approach produced good results. Nevertheless, additional advanced training on more intricate images is required to better the model's capacity and consistency in detecting missing objects under an array of cases.

The objective of the research work in points to be added here by highlighting the novelty of the proposed idea

3. Proposed Model

In the context of remote areas, the detection of missing cars presents a unique challenge, particularly when relying completely on GPS technology. The conventional approach involves the car owner filing a missing report at the nearby police station, which subsequently deploys a search team to locate the vehicle. However, this method often relies on a brute-force approach, where authorities use the limited information provided by the car owner to conduct a widespread search.

In the proposed model, the system aims to enhance and optimize the existing process for locating missing vehicles in remote areas, addressing the limitations of the current methodology. The proposed system relies on CCTV footage as the source to locate the car, where the system initiates the search for the missing car. The basic information for the car will be provided by the car owner with some reference images of the car. Utilizing CCTV footage the processing will be done to track the car's location and produce a route map of the path it took.

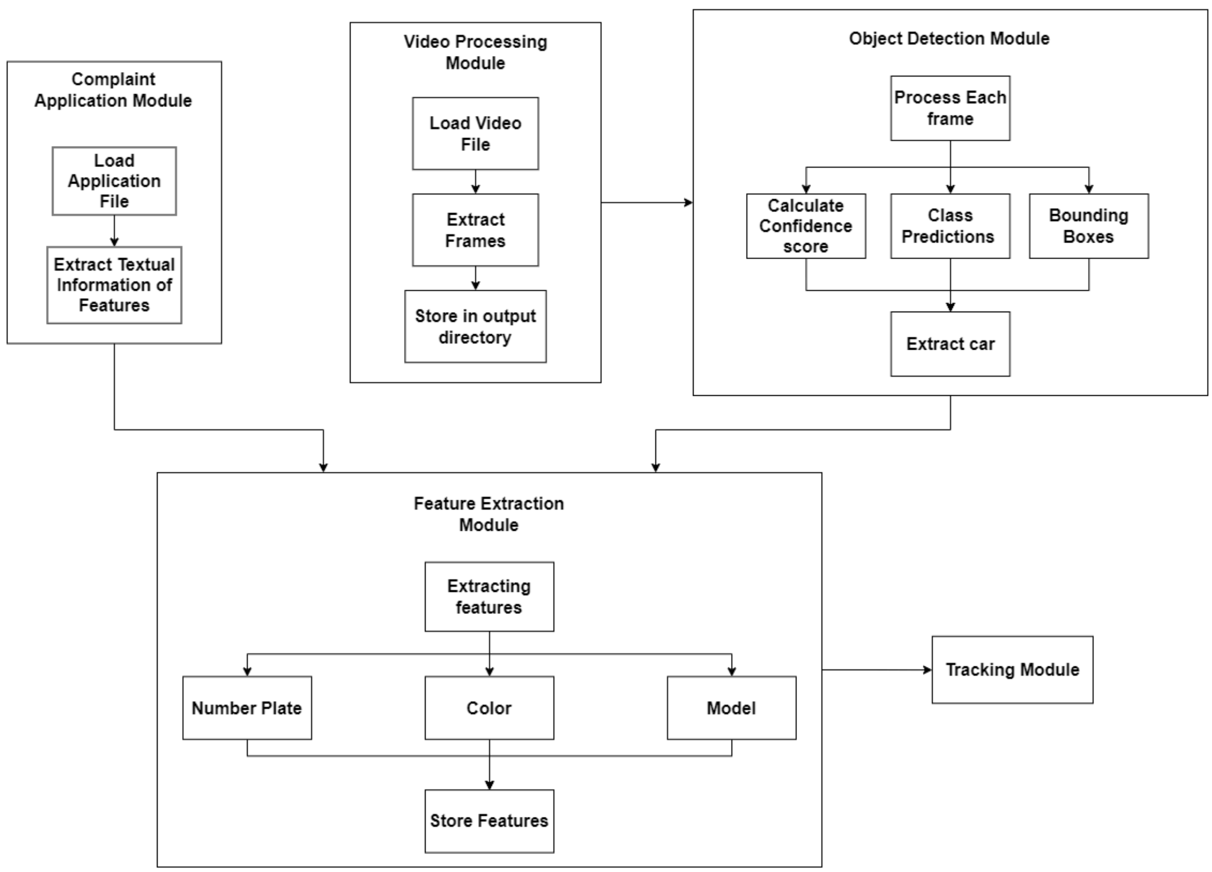


Figure 1: Modular Diagram of the missing car detection model

The proposed solution uses five modules, as shown in Figure 1. The applicant of the complaint uses an online form to enter the necessary details to initiate the search process. The form includes fields like Car Model, Car colour, Licence plate number, an optional field to upload the image of the car, the approximate timestamp at which the car has gone missing and the approximate location of the car. The textual information is mapped with the pre-fed image data to produce a reference image of the stolen car. This information is stored for further usage in the search process.

Based on the location and timestamp of theft, the video processing module extracts the videos of appropriate intervals and locations from the CCTV systems, preprocesses them and converts them into frames for further analysis.

Object Detection Module uses the extracted frames to identify cars using the YOLOv7 pre-trained model. The YOLOv7 internally calculates the confidence score, performs class prediction and assigns bounding boxes to identify all the candidate cars in the frame.

Confidence Score Calculation: It calculates a confidence score for each object or potential car within the frame. This score reflects the module's level of certainty that a particular region of the image contains a car. Higher confidence scores indicate a stronger belief that an object is a car.

Class Prediction: The module predicts the class of each object detected in the frame. In this specific case, the class of interest is "car." The module determines whether each object corresponds to a car or not.

Bounding Box Generation: Once an object is identified as a car, the module outlines or highlights it by drawing a bounding box around it. This bounding box visually encloses the detected car within the frame, making it easily distinguishable.

By performing the tasks mentioned above, the Object Detection Module identifies all candidate cars within the video frame. These candidates are regions within the image where the module has detected cars based on its analysis.

Further, the identified car images are extracted from the frame and sent for feature matching.

Feature Extraction Module

The Feature Extraction Module takes the cropped car images and extracts the features of the car. These features include the car model, car colour and the number plate. The extracted features are used to match the car image with the subject car features as provided by the applicant These features are also used when the car has to be reidentified in subsequent videos. It identifies the target car from the set of candidate cars.

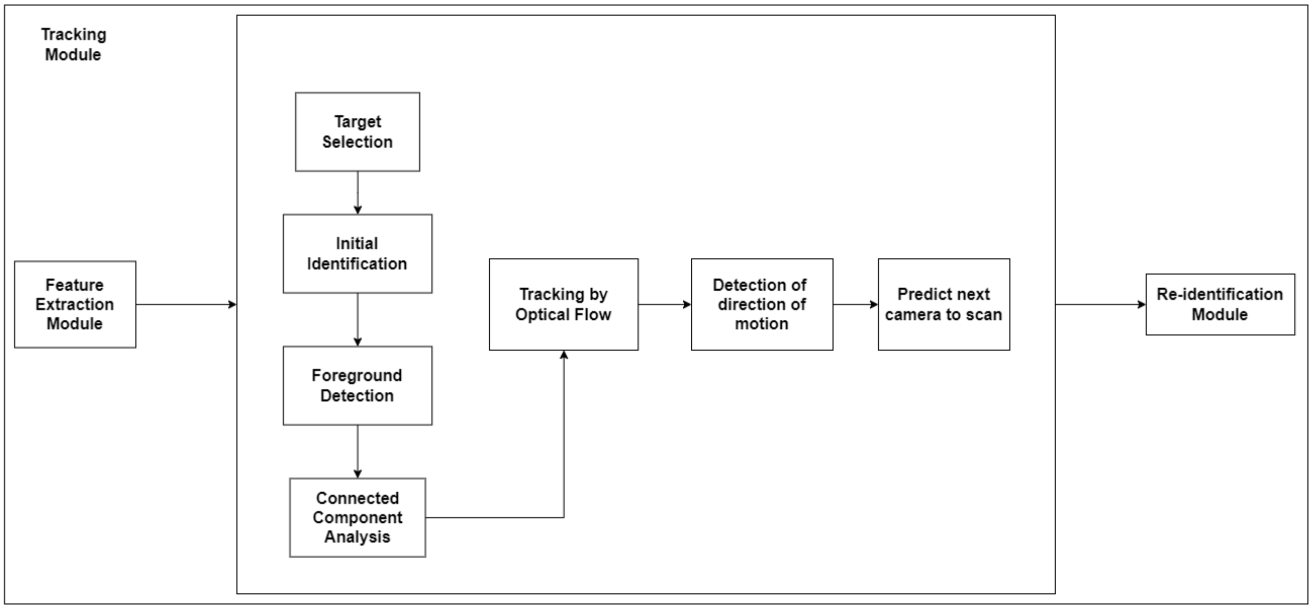


Figure 2: Tracking Module

Tracking Module:

This module serves the purpose of Tracking a car within the same video (inter-frame tracking).

The target car features from the previous frame are then used for identification of the same car in the next frame. It goes through the following steps.

Initial Identification: The module starts by identifying and tracking objects in one video frame. This initial identification may involve detecting cars or other objects in the frame and assigning unique identifiers or labels to them.

Foreground Detection: It may perform foreground detection to isolate moving objects from the static background. This step helps in distinguishing the objects of interest (e.g., cars) from the background.

Connected Flow Analysis: The module analyses the flow of connected objects across frames. It tracks how objects move from one frame to the next, allowing it to follow the trajectory of each object.

Tracking by Optical Flow: Optical flow is a technique used to estimate the motion of objects in consecutive video frames. It calculates how pixels move between frames, helping to track the objects' positions accurately over time.

Detection of the direction of motion: The direction of motion of the car helps in identifying the next camera or the set of cameras that might have captured the car. The direction of motion is calculated using vector mathematics.

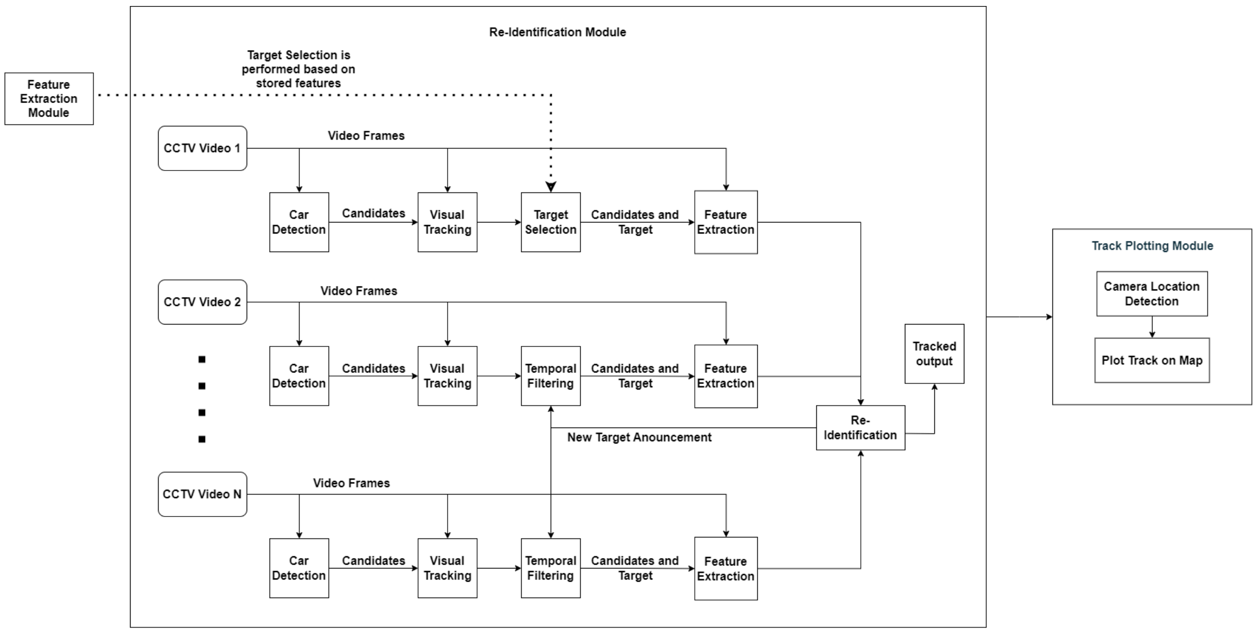


Figure 3: Re-Identification Module

Re-Identification Module:

This module serves the purpose of tracking of car from multiple CCTV footage videos captured at different locations (intervideo tracking).

When a car exits one camera coverage it has to be identified in another camera coverage. The identification module calculates similarity scores between the car identified in the last frame of the previous video and the cars in the first frame of the new video. This score is based on the features of the car extracted from the feature extraction module.

Reidentification is the process of associating an object identified in one video source with the same object in another video source. It helps in maintaining tracking across video boundaries.

Track Plotting Module:

This module detects the location of the cameras in which the car has been found and then plots the track on a map.

4. Methodology

The methodology of the project is as follows:

4.1 Video Processing Module

In the video processing module video from CCTV is uploaded to the system and then video processing is done, where the frames are converted from the video and stored in one folder.

4.2 Object Detection Module

Each frame undergoes analysis in the object detection module, if any particular frame does not contain objects(cars) then delete the frame. This helps to reduce the complexity in cases of no vehicles in videos. The module uses the YOLO model for vehicle detection. Then after cleaning through the frame data the system starts detecting cars in each frame and creates a bounding box that crops the cars from the frame. The cropped cars are stored in another folder. Additionally, the cropped cars are checked with a number plate in the frame, if a number plate is detected then these number plates are also cropped and stored.

4.3 Feature Extraction Module

The cropped cars and number plates are sent to extract the features of the car such as car model, colour, texture and number plate. This feature extraction is done with the user input image also. Car models and colours are extracted using the CNN model EfficientNet B1. The cropped number plates are passed under OCR.

Can add info about deskewing technique for better OCR results

4.3.1 EfficientNet

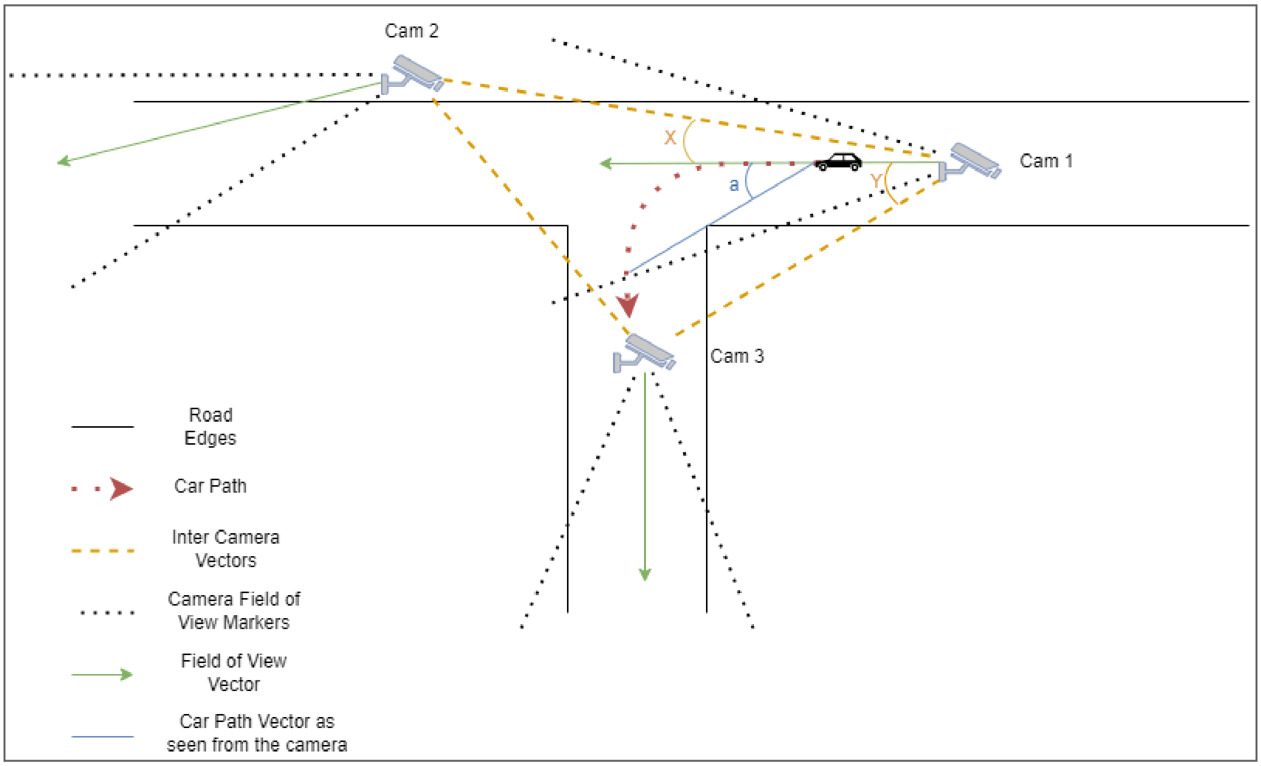
EfficientNet is a convolution neural network that works on the concept of compound scaling.

The compound scaling method is based on the idea of balancing dimensions of width, depth, and resolution by scaling with a constant ratio. This capability allows the system to train the model efficiently, minimizing any additional loss during the training process. Our dataset is employed for training models specifically designed for car colour and model classification. The training process involves instructing the model to classify cars into distinct colour classes and model classes.

4.3.2 Easy OCR

Easy OCR is a font-dependent printed character reader based on a template-matching algorithm.

4.4 Tracking Module



This is the most important module as it produces the tracking results that help the officials find the stolen vehicle. The tracking is split into three parts, the car direction detection, the next camera decision-making, and the track plotting.

4.4.1 Car Direction Detection

The process starts by scanning through the CCTV camera footage of the nearest camera from the location of the theft. Once the suspect vehicle is identified in the footage, it is tracked using an object tracking algorithm, ‘DeepSort’, to produce a track of the path travelled by the vehicle as seen by the camera. We use the first and last coordinates of the centroid centre of the car bounding box and create a vector. This vector is compared with the direction vector of the field-of-view of the camera to decide whether the car takes a turn in a specific direction or moves straight.

4.4.2 Next Camera to Choose

Direction vectors between cameras (inter-camera vectors) are created beforehand using the latitude and longitude of each camera. For each inter-camera vector between the current camera and the neighbouring cameras, its angle with the direction vector of the current camera is found. These angles are compared with the angle between the car direction vector and the field-of-view vector of the camera. Next camera is chosen based on the least difference between these two angles in the appropriate direction.

4.4.3 Track plotting

The above process is applied to subsequent cameras to track the car as far as possible in the CCTV network. Finally, the track is created using the geolocations of each camera that tracked the subject car to produce a complete route map of the path taken by the car. This route is plotted using map APIs like Google Maps.

5. Implementation

Video Processing

Consider this a frame extracted from the video. This frame is used for further processing to demonstrate the implementation of the project.

Figure 4: Output frame of test video from CCTV

The frame contains 3 cars, 2 are appearing completely and one is partially
Here are Cropped Cars are

		
Figure 5a. Car 1	Figure 5b. Car 2	Figure 5c. Car 3

Number Plate from Figure

Figure 6

Car Model Prediction:

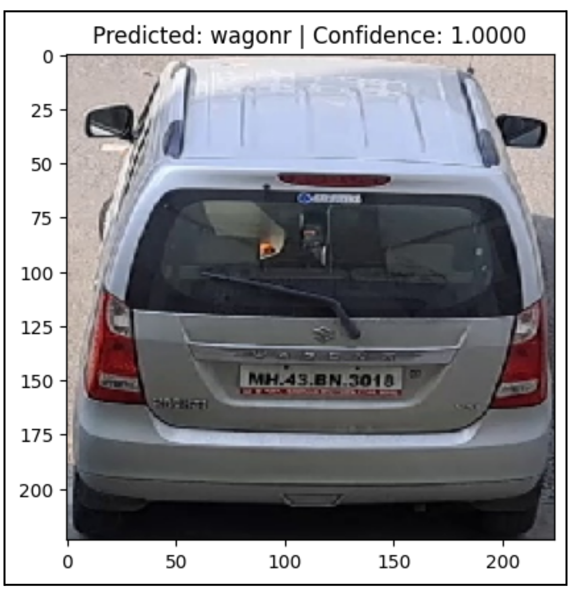


Figure 7.1 Car Model Prediction

Car Color Prediction:

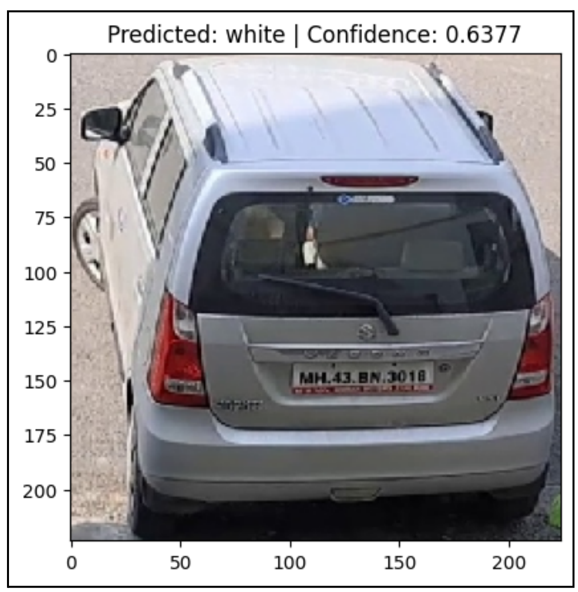


Figure 7.2 Car Color Prediction

6. Result

7. Conclusion

The persistent challenge of vehicle theft demands innovative solutions, particularly as criminals adapt to technological advancements. The integration of artificial intelligence and computer vision with existing surveillance infrastructure offers a promising approach to combat this crime effectively. By automating the analysis of CCTV footage, law enforcement agencies can swiftly detect, identify, and track stolen vehicles, significantly enhancing their ability to apprehend suspects and recover stolen property. Moreover, the application of AI-powered systems enables proactive measures by identifying patterns and anomalies in vehicle behavior, thereby aiding in the prediction and prevention of future thefts. In remote areas where traditional methods may prove inadequate, leveraging CCTV footage as a primary source for locating missing vehicles presents a viable alternative, optimizing the search process and mitigating the limitations of GPS technology. Ultimately, these advancements enhance law enforcement capabilities and serve as a deterrent to potential offenders, fostering a safer and more secure society.

8. References

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