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AUTOMATED HELMET DETECTION AND CITATION SYSTEM USING LICENSE PLATE RECOGNITION

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ABSTRACT

The rising affordability of motorcycles has made them an increasingly popular choice for daily transportation. While this trend offers many benefits, including reduced commuting costs and enhanced mobility, it has also led to a concerning increase in motorcycle accidents. A significant factor contributing to these incidents is the alarming number of riders who neglect to wear helmets. This oversight not only endangers the lives of motorcyclists but also poses a broader risk to public safety on our roads.

In response to this critical issue, governments have implemented laws designating it a punishable offense to ride without a helmet. Although existing video surveillance systems have been useful in monitoring compliance, they rely heavily on human intervention. This dependence can lead to inefficiencies over time, as well as potential biases in enforcement, which undermine the effectiveness of these measures.

To combat these challenges, we propose an innovative solution: an automated system designed for real-time detection of motorcyclists riding without helmets through advanced surveillance video analysis. Our approach encompasses several key components:

1. **Motorcycle Detection:** *We utilize background subtraction techniques combined with machine learning algorithms to accurately identify motorcycles within surveillance footage. This allows for precise monitoring of areas with high traffic volumes.*
2. **Helmet Classification:** *Upon detecting a motorcycle, we implement advanced edge detection algorithms—leveraging both first-order and second-order derivatives—to ascertain whether the rider is wearing a helmet. This classification process is further enhanced using deep learning neural network models, which significantly improve the accuracy of our detections by minimizing false positives and negatives.*
3. **License Plate Recognition:** *If a rider is identified as not wearing a helmet, our system employs Optical Character Recognition (OCR) alongside neural networks to capture and recognize the vehicle's license plate. This capability ensures that offenders can be traced and held accountable.*
4. **Evidence Collection:** *Beyond simply identifying violations, our system archives frames from the video where the rider is seen without a helmet.*

These frames serve as irrefutable digital evidence for enforcement purposes, aiding in the prosecution of non-compliant riders.

By automating this detection process, our system empowers governmental authorities to efficiently issue fines to those who fail to comply with helmet laws. This not only ensures accountability but also promotes safer

riding practices among motorcyclists. Furthermore, it communicates to the community that vigilant monitoring is ongoing, even during off-peak hours, thus enhancing the perceived risk of non-compliance.

In conclusion, our proposed solution marks a significant advancement in road safety technology. By integrating real-time monitoring with automated enforcement mechanisms, we can better protect motorcyclists and foster a culture of compliance with safety regulations. Ultimately, this initiative has the potential to reduce accident rates, save lives, and create a safer environment for all road users.

INTRODUCTION

L.L What is Object Detection?

Object detection remains a pivotal challenge in the field of computer vision, focusing on the identification and localization of objects from predefined classes within images. This process can be approached through various methodologies, including the creation of bounding boxes that encapsulate detected objects and more sophisticated techniques like segmentation, which involves marking every pixel in an image that corresponds to a particular object. The evolution of object detection has been dramatic, especially with the rise of Convolutional Neural Networks (CNNs), which have transformed how we extract complex features from images. However, revisiting traditional methods offers valuable insights and innovative inspiration for modern applications. Before the deep learning revolution, object detection relied on a multi-step process. This began with edge detection and feature extraction techniques, such as Scale-Invariant Feature Transform (SIFT) and Histogram of Oriented Gradients (HOG).

These methods enabled the extraction of meaningful features, which were then matched against established object templates at various scales to effectively detect and localize objects within images.

It's crucial to differentiate between related concepts in this domain. **Image classification** involves assigning a single class label to an entire image, while **object localization** focuses on drawing bounding boxes around one or more objects within that image. Object detection, being inherently more complex, integrates both tasks—detecting multiple objects, localizing each with bounding boxes, and assigning appropriate class labels. Collectively, these endeavors fall under the broader umbrella of **object recognition**.



Object Detection

As technology has advanced, so have the techniques for object detection. Recent models like YOLO (You Only Look Once), SSD (Single Shot MultiBox Detector), and Faster R-CNN have pushed the boundaries of what's possible in terms of speed and accuracy. These architectures leverage deep learning to achieve real-time processing capabilities, making them suitable for applications ranging from autonomous vehicles and drones to surveillance systems and robotics.

Moreover, the importance of object detection extends beyond mere identification and classification. It plays a critical

role in enhancing our interaction with visual data, enabling machines to interpret and respond to their environments in ways that were previously

unimaginable. For instance, in autonomous driving, accurate object detection is essential for recognizing pedestrians, vehicles, and obstacles, thereby ensuring safety on the roads. In surveillance, it helps in identifying suspicious activities or tracking individuals across different camera feeds.

In summary, object detection is a multifaceted aspect of computer vision that requires the integration of classification and localization techniques to effectively analyze and interpret visual information. Its significance spans a wide array of applications, highlighting its crucial role in advancing technology and enhancing our engagement with the world around us. As research continues to progress and new methodologies emerge, the future of object detection promises even greater advancements, paving the way for innovative solutions that will further shape our interactions with visual data.

LITERATURE SURVEY

J. Chiverton , “Helmet presence classification with motorcycle detection and tracking” IET, 2012 This paper J. Chiverton proposed system such that the past few years, many algorithms and models have been used for helmet detection, but this paper is used the background subtraction method to separate the background of the bikers and then isolate the head of the biker and identify the features of the helmet. It uses Referred following Techniques : 1.Helmet Detection.

2. Motorcycle detection and tracking. This system only detect helmet and number plate but does not sending alert to the motorcyclist

. Z. Chen , “Vehicle detection, tracking” in Procs. of the IEEE Int. This paper Z. Chen proposed system such as Propose to used a Multi-dimensional Gaussian Kernal Density Transform and a self-adaptive Gaussian mixture model for background subtraction. This paper presents an improved GMM algorithm that is less sensitive to sudden changes in the global illumination compared to the GMM presented in the paper. It employs a spatio-temporal Gaussian smoothing algorithm and a self-adaptive GMM for background modeling. Geometrical features to identify a helmet, it can detect any other object as a helmet.

C. Patel, “Automatic Number Plate Recognition System” This paper C. Patel proposed system evaluates the trichromatic imaging with a color-discrete characteristic approach can provide promising results for number plate detection. Some characteristics are 1. Number plate detection. 2.Recognizing the number plate characters Color is a noteworthy part of our visual experience. It can affect how we interpret things about the world, influence our appetite and mood, and even carry symbolic meaning for some people.

METHODS AND TECHNIQUES USED

What is YOLOv3?

Imagine how effortless our lives could be if we could simply leverage an existing framework, execute it, and achieve our desired outcomes—minimal effort for maximum reward. This ideal is something we all strive for in our respective professions, as it allows us to focus on innovation and creativity rather than getting bogged down by the intricacies of foundational work.

I feel incredibly fortunate to be part of the vibrant machine learning community, where even the largest tech companies actively embrace open-source technologies. The collaborative spirit of this community is inspiring, as it fosters an environment where knowledge and tools are shared freely. While it is essential to thoroughly understand the underlying concepts before implementing them, having foundational work provided by leading data scientists and researchers greatly accelerates our ability to innovate.

This is particularly true in deep learning fields such as computer vision. Many individuals and organizations do not have access to the vast computational resources or the time required to build deep learning models from scratch. This is where predefined frameworks and pretrained models prove invaluable, enabling users to harness the power of advanced algorithms without needing to start from the ground up.

In this context, we will explore one such powerful framework for object detection: **YOLO (You Only Look Once)**. Specifically, **YOLOv3** stands out as a remarkably fast and accurate object detection framework that has transformed the landscape of real-time applications.

What sets YOLOv3 apart is its innovative approach of employing a single neural network to predict bounding boxes and class probabilities directly from full images. This architecture minimizes processing time while maximizing detection performance, making it particularly well-suited for real-time scenarios. YOLOv3 divides the input image into a grid and predicts bounding boxes and class probabilities for each grid cell, enabling it to detect multiple objects simultaneously.

As we delve deeper into YOLOv3, we will uncover the innovations that make it a game-changer in the realm of object detection. For instance, the introduction of multi-scale predictions allows YOLOv3 to detect objects at various sizes more effectively. By leveraging feature maps from different layers of the network, it can better handle both small and large objects, which is crucial for applications in autonomous driving, robotics, and video surveillance.

Furthermore, the integration of advanced techniques such as residual connections enhances the model's ability to learn complex features, contributing to improved accuracy and robustness. With its real-time processing capabilities, YOLOv3 has become a go-to choice for developers and researchers aiming to implement efficient object detection solutions.

In summary, the advancements represented by frameworks like YOLOv3 highlight the incredible potential of leveraging existing tools in the machine learning space. By utilizing pretrained models and open-source technologies, we can achieve remarkable outcomes with significantly reduced effort. As we continue to explore and innovate within this dynamic field, the possibilities for applying object detection in various domains are limitless, paving the way for smarter and more efficient systems that enhance our everyday lives.

3.1 How YOLO is Useful

. The R-CNN family of techniques, as discussed in Part 1, primarily utilizes region proposals to localize objects within an image. These methods focus on specific parts of the image deemed likely to contain objects, which can lead to a significant drawback: the potential loss of contextual information from the surrounding areas. This selective focus can hinder the model's ability to understand the broader scene, which is often crucial for accurate detection in complex environments.

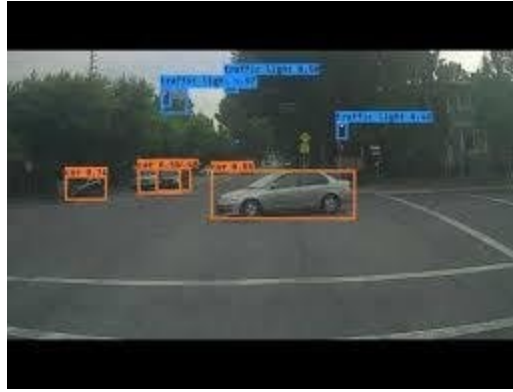


Fig yolo step1

In contrast, the YOLO (You Only Look Once) framework represents a paradigm shift in object detection methodologies. YOLO analyzes the entire image in a single pass, predicting both the bounding box coordinates and class probabilities for all potential objects present. This holistic approach not only enhances efficiency but also ensures that the model retains a comprehensive understanding of the context within the image. This is particularly beneficial in scenarios where the spatial relationship between objects plays a critical role in accurate detection.

One of the standout features of YOLO is its remarkable speed. Capable of processing up to 45 frames per second, YOLO allows for real-time applications, making it an ideal choice for dynamic environments such as autonomous vehicles, drone surveillance, and smart security systems. The ability to deliver rapid predictions without compromising accuracy positions YOLO as a leading algorithm in the object detection landscape.

Furthermore, YOLO's ability to generalize object representations is a key factor in its effectiveness. By leveraging a unified architecture, it achieves performance levels that are comparable to those of R-CNN algorithms while benefiting from

enhanced speed and efficiency. This makes YOLO a versatile tool for a wide range of applications, from robotics to augmented reality.

In the sections that follow, we will delve deeper into the various techniques employed within the YOLO algorithm. We will explore how YOLO utilizes anchor boxes and grid-based predictions to optimize object detection. Inspired by Andrew Ng's course on Object Detection, which has significantly enriched my understanding of YOLO's workings, we will uncover the innovations that make this framework a game-changer in the field.

Additionally, we will examine the subsequent iterations of YOLO, including YOLOv2 and YOLOv3, which introduced further enhancements such as improved feature extraction and multi-scale detection capabilities. These advancements have solidified YOLO's position at the forefront of object detection technologies, demonstrating its adaptability and effectiveness in tackling real-world challenges.

As we explore these developments, we will also discuss the practical implications of YOLO's speed and accuracy in various industries, such as healthcare diagnostics, retail analytics, and traffic monitoring. The ongoing research and evolution of YOLO highlight its potential to revolutionize how we approach object detection, paving the way for smarter, more responsive systems in an increasingly interconnected world.

In summary, the transition from R-CNN to YOLO marks a significant advancement in the field of object detection. By combining speed, accuracy, and a holistic understanding of images, YOLO not only meets the demands of modern applications but also sets the stage for future innovations. As we continue to explore the capabilities of this remarkable framework, the possibilities for its application are virtually limitless, promising a future where intelligent systems can better interpret and interact with the visual world around us.

RESULTS

We begin our process with a testing video, aptly named "bike1," which features a motorcycle rider not wearing a helmet. The primary objective of this project is to accurately detect the non-helmeted rider, recognize their motorcycle's number plate, and digitally retrieve this information while capturing the specific frame from the video where the violation occurs.

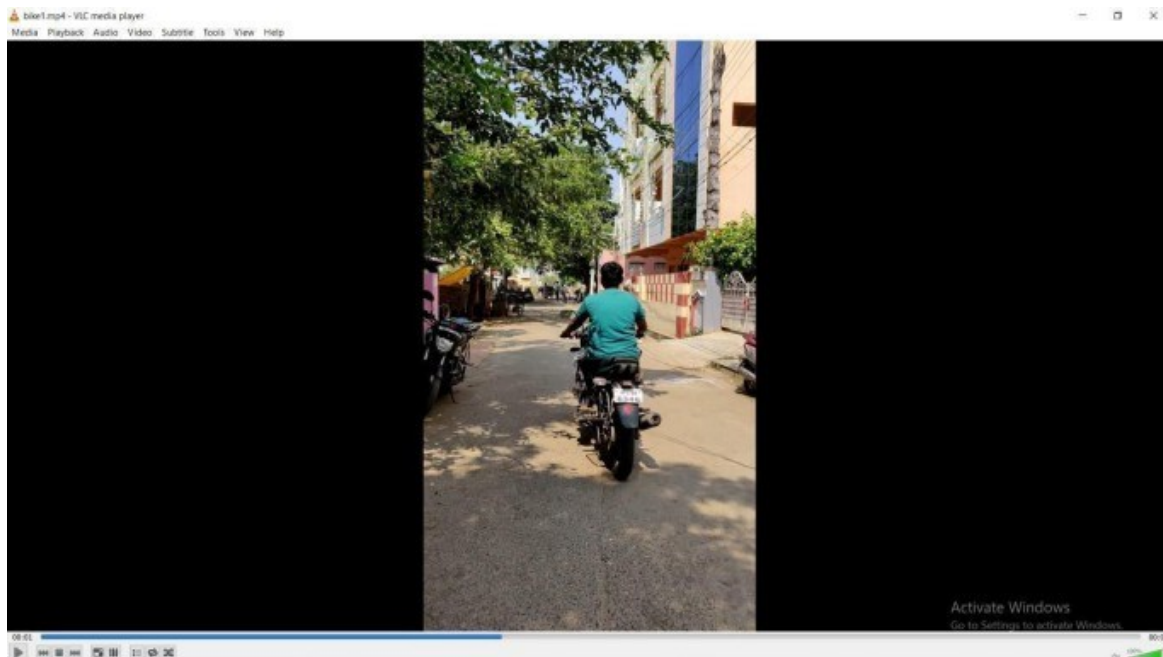


Fig 4.1 video snapshot

The video is processed by dividing it into frames, typically at a rate of one frame per second. Each frame is then analyzed using pre-defined trained weights embedded in the code. These weights are essential as they have

already been trained on a dataset containing various images of motorcycles, helmets, and riders—both with and without helmets. This allows the model to recognize and classify the relevant objects effectively without the need for retraining.

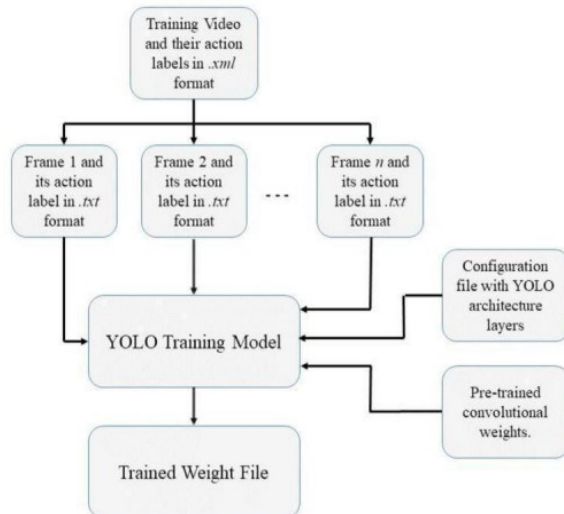


Fig 4.2 training weigh

```

13 from os.path import join, isfile, isdir
14 sys.path.append(r'..')
15 from object_detection.utils import label_map_util
16 from object_detection.utils import visualization_utils as vis_util
17 MODEL_NAME = 'inference_graph'
18 VIDEO_NAME = 'test1.mp4'
19 CWD_PATH = os.getcwd()
20 PATH_TO_SCRIPT = os.path.join(CWD_PATH, MODEL_NAME, 'inference_graph.pb')
21 PATH_TO_LABELS = os.path.join(CWD_PATH, 'training', 'labelmap.pbtxt')
22 PATH_TO_VIDEO = os.path.join(CWD_PATH, VIDEO_NAME)
23 NUM_CLASSES = 4
24 label_map = label_map_util.load_labelmap(PATH_TO_LABELS)
25 categories = label_map_util.convert_label_map_to_categories(label_map, max(num_classes+NUM_CLASSES, 0), display_name=True)
26 category_index = label_map_util.create_category_index(categories)
27 detection_graph = tf.compat.v1.Graph()
28 with detection_graph.as_default():
29     sess = tf.compat.v1.Session(detection_graph)
30     with tf.compat.v2.GraphDef():
31         with tf.compat.v2.in_gfile(PATH_TO_SCRIPT, 'r') as fid:
32             serialized_graph = fid.read()
33             sess.graph_def.ParseFromString(serialized_graph)
34             tf.import_graph_def(sess.graph_def, name='')
35     sess = tf.compat.v1.Session(detection_graph)
36     for i in range(10):
37         img = cv2.imread(PATH_TO_VIDEO)
  
```

```

Run:
[{"processing_time": 48.564, "results": [{"xmin": 860, "xmin": 3404, "xmax": 1899, "ymax": 3532}], [{"plate": "ap2786344"}],
The bike number is ap2786344
pass to number plate ap2786344
Without helmet Number plate
Iteration 12: 38.397 sec
Creating...frame.jpg
Process finished with exit code -1
  
```

Fig 4.3 creating frames

Once the video frames are fed into the YOLOv3 model, it identifies and detects all five custom classes we have trained the model on. Among these classes is the "person" class, which encompasses riders and pedestrians. If a rider is detected without a helmet, the model will then extract additional class information about that rider, including their associated license plate.

The detection process hinges on determining whether the coordinates of the non-helmet class fall within the bounds of the person class. This spatial relationship is crucial for accurately associating the detected helmetless rider with their vehicle.



Fig 4.4 output Frame

As the trained model processes each frame, it can distinguish between the various classes, enabling us to obtain counts of both riders and helmets. If the system identifies a rider on a two-wheeler who is not wearing a helmet, it proceeds to the next step—retrieving the license plate information for further action.

In summary, this methodology not only enhances road safety by identifying violations but also leverages advanced computer vision techniques to automate the detection process, ensuring that our roads are monitored efficiently.

4.1 Automated Citation System Implementation with YOLO:

YOLOv3 is a state-of-the-art object detection model that can be used for license plate detection and recognition. Here's a basic outline of the implementation:

1. **Data Collection:** Collect a dataset of vehicle images with annotated license plate regions.
2. **Model Training:** Train a YOLOv3 model on the collected dataset to detect and localize license plates.
3. **License Plate Extraction:** Use the trained model to extract license plate regions from real-time video feeds or captured images.
4. **Character Recognition:** Apply OCR techniques to recognize the characters on the extracted license plates.
5. **Database Integration:** Integrate the recognized license plate numbers with a database of vehicle registrations and traffic violations.
6. **Citation Generation and Notification:** Automatically generate citations for detected violations and

```
import cv2
import torch
# Load the YOLOv3 model
model = torch.hub.load('ultralytics/yolov3', 'yolov3n')
# Process the image
img = cv2.imread('image.jpg') results =
model(img)

# Extract detected license plates

for *xyxy, conf, cls in results.xyxy[0]:
    x1, y1, x2, y2 = int(xyxy[0] * img.shape[1]), int(xyxy[1] * img.shape[0]), int(xyxy[2] * img.shape[1]), int(xyxy[3] * img.shape[0])
    crop_img = img[y1:y2, x1:x2]
    # Apply OCR to recognize characters on the cropped license plate image # ...

    # Check against the database and generate citation if necessary # ...
```



CONCLUSION AND FUTURE WORK

CONCLUSION

In this project, we have developed a comprehensive framework for the automatic detection of motorcycle riders without helmets using CCTV footage, alongside an automated vehicle license plate retrieval system. By employing YOLOv3 and advanced transfer learning techniques, we achieved an outstanding detection accuracy of 98.72% for identifying motorcyclists who are not adhering to safety regulations.

However, simply detecting non-compliant riders is not enough for effective enforcement. To address this, our system includes a robust mechanism for recognizing and storing the license plates of these motorcycles. This functionality allows the Transport Office to seamlessly access their database of licensed vehicles, facilitating efficient follow-up actions. Authorities can then impose penalties on motorcyclists who violate safety regulations, ultimately contributing to enhanced road safety.

Moreover, our innovative approach not only promotes adherence to safety regulations but also fosters a culture of responsible riding within the community. By combining cutting-edge technology with practical enforcement strategies, we aim to create a safer environment for all road users.

As we look to the future, we envision expanding this framework to include additional safety features, such as real-time alerts for authorities when violations occur. We also plan to explore partnerships with local government agencies and advocacy groups to raise awareness about helmet use and its importance in preventing accidents.

In summary, our project stands as a significant step forward in using technology for public safety. By effectively integrating automatic detection and data retrieval, we are paving the way for a more secure and responsible riding environment, ultimately leading to a reduction in motorcycle-related accidents and injuries.

FUTURE WORK

The proposed system effectively addresses several challenges in detecting motorcyclists with and without helmets, overcoming issues related to image quality, lighting variations, and minor changes in angles. As we look to the future, there are numerous promising directions for expanding this project.

One potential avenue is the application of similar detection methodologies to monitor vehicles that violate traffic regulations. This could include identifying cars that disregard traffic signals, speed limits, or parking rules. By deploying this technology, we could more effectively identify drivers who disrupt traffic flow or cause damage to surrounding vehicles, particularly in parking lots and urban areas.

Furthermore, our detection and license plate recognition capabilities could significantly streamline toll collection processes. By automatically identifying vehicles as they approach toll booths, the system could help reduce traffic congestion and minimize operational delays often caused by server malfunctions or manual collection methods. This enhancement could lead to a smoother flow of traffic, ultimately improving the overall efficiency of toll operations.

Additionally, there is potential to integrate our system with broader smart city initiatives. By collaborating with traffic management systems, we could create a cohesive framework that not only monitors compliance but also provides valuable data for urban planning and infrastructure improvements.

Overall, the future of this project lies in its adaptability and the diverse applications it can support. From traffic enforcement and parking management to smart city integrations, our goal is to enhance road safety and operational efficiency. As we continue to innovate and refine our technology, we aim to contribute meaningfully to safer, more efficient urban environments for everyone.

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