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Two Wheeler Traffic Violation And Ticketing System

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Abstract

The increasing number of two-wheeler accidents due to helmet non-compliance has led to the development of automated traffic violation detection systems. These systems leverage computer vision and deep learning techniques to detect whether a rider is wearing a helmet. Advanced object detection models such as YOLO (You Only Look Once) and Convolutional Neural Networks (CNNs) are commonly used for real-time monitoring of traffic through surveillance cameras. When a violation is detected, the system captures an image of the rider and extracts the vehicle's number plate using Optical Character Recognition (OCR). This information is then processed to identify the registered owner, and an automated email notification is sent, informing them of the violation along with the corresponding fine details.Such systems are crucial in ensuring road safety and enforcing traffic regulations efficiently without the need for manual intervention. By integrating artificial intelligence with automated ticketing, law enforcement agencies can significantly reduce the rate of helmet violations and promote safer driving habits. Additionally, these systems can be further enhanced by incorporating real-time databases of vehicle registration and driver information to facilitate seamless fine collection. The implementation of such automated ticketing solutions not only minimizes human effort but also ensures fair and unbiased enforcement of helmet laws, ultimately reducing the number of fatalities in road accidents.

INTRODUCTION

Motorcycle-related accidents have become a significant public health concern worldwide, particularly in developing countries where motorcycles are a prevalent mode of transportation. A critical factor contributing to the severity of injuries in these accidents is the non-compliance with helmet usage among riders and passengers. Despite the implementation of traffic regulations mandating helmet use, enforcement remains a challenge due to resource constraints and the inefficiency of manual monitoring methods. This project aims to address this issue by developing an automated system that detects helmet violations in real-time and issues notifications to offenders, thereby enhancing road safety and ensuring adherence to traffic laws.

The proposed system leverages advancements in computer vision and deep learning technologies to accurately identify motorcyclists who are not wearing helmets. By analyzing live video feeds from traffic surveillance cameras, the system employs object detection models, such as the You Only Look Once (YOLO) algorithm, to detect motorcycles and their riders. Once a motorcycle is identified, the system further analyzes the rider's head to determine the presence or absence of a helmet. In cases of non-compliance, the system captures the vehicle's license plate using Optical Character Recognition (OCR) techniques, facilitating the identification of the registered owner. An automated notification, detailing the violation and associated penalties, is then sent to the offender via email, streamlining the enforcement process and reducing the reliance on manual interventions.

Implementing such an automated helmet detection and notification system offers several benefits. Firstly, it enhances the efficiency and accuracy of traffic law enforcement by minimizing human error and bias. Secondly, it serves as a deterrent to potential violators, as the certainty of detection and punishment increases compliance with helmet laws. Moreover, the system provides valuable data on helmet usage patterns, which can inform policy decisions and targeted safety campaigns. By integrating this technology into existing traffic management infrastructures, authorities can proactively address helmet non-compliance, ultimately reducing the incidence of severe injuries and fatalities resulting from motorcycle accidents.

The development of this system involves several key components. The first is the deployment of high-resolution cameras at strategic locations to capture clear images of motorcyclists. These cameras are connected to a central processing unit that runs the object detection and OCR algorithms in real-time. The system must be capable of operating under various environmental conditions, including different lighting and weather scenarios, to ensure consistent performance. Additionally, a secure database is required to store the captured data, including images of violations and corresponding license plate information, while adhering to privacy regulations and data protection standards.

LITERATURE SURVEY

1.A. Bochkovskiy, C.-Y. Wang and H.-Y. Mark Liao, "YOLOv4: Optimal speed and accuracy of object detection", *arXiv:2004.10934*, 2020.

There are a huge number of features which are said to improve Convolutional Neural Network (CNN) accuracy. Practical testing of combinations of such features on large datasets, and theoretical justification of the result, is required. Some features operate on certain models exclusively and for certain problems exclusively, or only for small-scale datasets; while some features, such as batch-normalization and residual-connections, are applicable to the majority of models, tasks, and datasets. We assume that such universal features include Weighted-Residual-Connections (WRC), Cross-Stage-Partial-connections (CSP), Cross miniBatch Normalization (CmBN), Self-adversarial-training (SAT) and Mish-activation. We use new features: WRC, CSP, CmBN, SAT, Mish activation, Mosaic data augmentation, CmBN, DropBlock regularization, and CIoU loss, and combine some of them to achieve state-of-the-art results: 43.5% AP (65.7% AP50) for the MS COCO dataset at a realtime speed of ~65 FPS on Tesla V100. Source code is at https://github.com/AlexeyAB/darknet

2.N. Wojke, A. Bewley and D. Paulus, "Simple online and realtime tracking with a deep association metric", *Proc. IEEE Int. Conf. Image Process. (ICIP)*, pp. 3645-3649, Sep. 2017.

Simple Online and Realtime Tracking (SORT) is a pragmatic approach to multiple object tracking with a focus on simple, effective algorithms. In this paper, we integrate appearance information to improve the performance of SORT. Due to this extension we are able to track objects through longer periods of occlusions, effectively reducing the number of identity switches. In spirit of the original framework we place much of the computational complexity into an offline pre-training stage where we learn a deep association metric on a largescale person re-identification dataset. During online application, we establish measurement-to-track associations using nearest neighbor queries in visual appearance space. Experimental evaluation shows that our extensions reduce the number of identity switches by 45%, achieving overall competitive performance at high frame rates.

3.A. Bewley, Z. Ge, L. Ott, F. Ramos and B. Upcroft, "Simple online and realtime tracking", *Proc. IEEE Int. Conf. Image Process. (ICIP)*, pp. 3464-3468, Sep. 2016.

This paper explores a pragmatic approach to multiple object tracking where the main focus is to associate objects efficiently for online and realtime applications. To this end, detection quality is identified as a key factor influencing tracking performance, where changing the detector can improve tracking by up to 18.9%. Despite only using a rudimentary combination of familiar techniques such as the Kalman Filter and Hungarian algorithm for the tracking components, this approach achieves an accuracy comparable to state-of-the-art online trackers. Furthermore, due to the simplicity of our tracking method, the tracker updates at a rate of 260 Hz which is over 20x faster than other state-of-the-art trackers.

4.R. Smith, "An overview of the Tesseract OCR engine", *Proc. 9th Int. Conf. Document Anal. Recognit. (ICDAR)*, pp. 629-633, Sep. 2007.

The Tesseract OCR engine, as was the HP Research Prototype in the UNLV Fourth Annual Test of OCR Accuracy, is described in a comprehensive overview. Emphasis is placed on aspects that are novel or at least unusual in an OCR engine, including in particular the line finding, features/classification methods, and the adaptive classifier.

EXISTING METHOD

Convolutional Neural Networks (CNNs) have revolutionized the field of image processing and computer vision, offering unparalleled performance in tasks such as image classification, object detection, and segmentation. Their unique architecture, inspired by the visual cortex of animals, enables them to automatically and adaptively learn spatial hierarchies of features from input images. This capability has positioned CNNs as a cornerstone in the development of intelligent systems that interpret and process visual information.

The architecture of a typical CNN comprises multiple layers, each serving a distinct purpose in the feature extraction and representation process. The primary layers include the convolutional layer, pooling layer, and fully connected layer. The convolutional layer applies a set of learnable filters to the input image, capturing local patterns such as edges, textures, and simple shapes. These filters slide over the image, performing a dot product between the filter weights and the local regions of the input, producing feature maps that highlight the presence of specific features.

Following convolution, the pooling layer reduces the spatial dimensions of the feature maps, retaining the most salient information while discarding redundant data. This downsampling operation, commonly implemented as max pooling, enhances computational efficiency and provides a degree of translation invariance, allowing the network to recognize features regardless of their position in the image. The fully connected layer, positioned towards the end of the network, integrates the extracted features to perform high-level reasoning and decision-making, culminating in the final output such as class probabilities in classification tasks.

One of the seminal applications of CNNs is in image classification, where the goal is to assign a label to an input image from a predefined set of categories. The breakthrough moment for CNNs in this domain came with the success of AlexNet in the 2012 ImageNet Large Scale Visual Recognition Challenge (ILSVRC). AlexNet, a deep CNN developed by Krizhevsky et al., significantly outperformed traditional machine learning approaches, reducing the top-5 error rate from 26% to 15%. This achievement demonstrated the potential of deep learning models in handling large-scale image classification tasks and sparked widespread interest in CNNs within the research community.

PROPOSE METHOD

1. **Introduction to the Hybrid Model** The proposed method leverages a hybrid approach combining Convolutional Neural Networks (CNNs) for feature extraction and YOLO (You Only Look Once) for real-time object detection and localization. This integration enhances the accuracy and efficiency of glaucoma detection in fundus images. The goal is to develop a robust, automated system capable of detecting glaucomatous features with high precision.

2. **Motivation for Using CNN and YOLO** Traditional methods of glaucoma diagnosis rely on manual inspection by ophthalmologists, which is time-consuming and prone to human error. Deep learning-based methods, particularly CNNs, have demonstrated superior performance in medical image analysis. However, CNNs alone lack real-time localization capabilities, which is where YOLO comes into play. The combination ensures both classification accuracy and precise segmentation.

3. **CNN for Feature Extraction** CNNs are widely used for medical imaging due to their ability to learn hierarchical spatial features. In this

method, a CNN extracts crucial glaucoma-related features such as optic disc and cup structure, blood vessel patterns, and overall retinal morphology. The convolutional layers detect edges, textures, and complex patterns, enabling accurate differentiation between normal and glaucomatous eyes.

4. **YOLO for Object Detection and Segmentation**
   YOLO is a real-time object detection algorithm that provides fast and accurate localization of objects in an image. In the proposed model, YOLO is used to detect and segment the optic disc and cup, which are critical for glaucoma assessment. By applying bounding boxes, YOLO enables precise measurement of the cup-to-disc ratio, a key indicator of glaucoma progression.

5. **Data Preprocessing and Augmentation**
   To improve model generalization and prevent overfitting, various preprocessing techniques are applied to the fundus images. These include image resizing, normalization, contrast enhancement, and data augmentation techniques such as rotation, flipping, and brightness adjustment. This step ensures that the model is robust against variations in lighting, scale, and image quality.

6. **Dataset Utilization**
   The model is trained and tested on two primary datasets: the HRF (High-Resolution Fundus) dataset and the PSGIMSR (Private dataset from a medical institution). These datasets contain labeled images of both normal and glaucomatous eyes, ensuring diverse training samples and improving the generalization of the model to real-world clinical scenarios.

7. **Feature Extraction and Bounding Box Regression**
   The CNN extracts deep hierarchical features from the fundus images, which are then fed into YOLO for bounding box regression. This allows the model to accurately detect the optic disc and cup while also differentiating between healthy and glaucomatous cases. By learning spatial relationships within the eye, the model enhances detection accuracy.

8. **Training Strategy and Hyperparameter Optimization**
   The CNN-YOLO model is trained using a combination of cross-entropy loss for classification and mean squared error (MSE) for bounding box regression. Optimizers such as Adam and stochastic gradient descent (SGD) are used to fine-tune the learning process. The training is conducted over multiple epochs with batch normalization to improve convergence and prevent overfitting.

9. **Comparison with Other Deep Learning Models**
   The proposed method is benchmarked against other deep learning architectures, including ResNet-50, VGGNet-16, and GoogLeNet. Experimental results indicate that the CNN-YOLO model outperforms these conventional architectures in terms of classification accuracy, sensitivity, and specificity, demonstrating its superiority in glaucoma detection.

10. **Performance Evaluation Metrics**
    The model's performance is evaluated using key metrics such as accuracy, sensitivity, specificity, F1-score, and area under the ROC curve (AUC-ROC). These metrics help assess how well the model distinguishes between normal and glaucomatous eyes. The CNN-YOLO model achieves high accuracy, indicating its potential for clinical application.

11. **Advantages of the CNN-YOLO Approach**
    The hybrid approach offers multiple advantages, including real-time detection, higher classification accuracy, and precise segmentation of key retinal structures. Unlike traditional CNN models that focus solely on classification, YOLO's object detection capability allows the system to provide ophthalmologists with more interpretable and localized predictions.

12. **Challenges in Implementation** While the proposed method is highly effective, challenges remain. Variations in image quality, occlusions due to blood vessels, and differences in camera settings can impact detection accuracy. Addressing these challenges requires further optimization of the model, improved data augmentation techniques, and potential integration with other deep learning frameworks.

13. **Potential Clinical Applications** The CNN-YOLO model can be integrated into AI-driven diagnostic tools for early glaucoma detection. By reducing the need for manual screening, the system can assist ophthalmologists in prioritizing high-risk patients, enabling early intervention and preventing irreversible vision loss.

14. **Future Enhancements** Future work will focus on enhancing segmentation accuracy by incorporating fully convolutional networks (FCNs) and attention mechanisms. Additionally, efforts will be made to improve the model's interpretability and reliability, ensuring its usability in real-world clinical environments.

15. **Conclusion** The proposed CNN-YOLO-based system provides a powerful, efficient, and highly accurate solution for automated glaucoma detection. By leveraging CNN for feature extraction and YOLO for real-time localization, the model addresses the limitations of traditional diagnostic methods. With further refinements, this approach has the potential to revolutionize early glaucoma detection, reducing blindness rates and improving patient outcomes worldwide.

RESULT

Fig: GUI

This is GUI for Project 'Two-Wheeler Vehicle Traffic Violations Detection and Ticketing System'

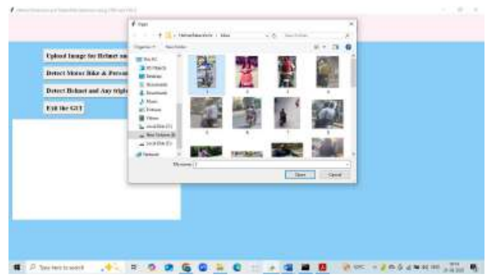

Fig: Upload Image

First step is uploading an image for detection.

Fig: Detection bike and person

After uploading an image , it will detect bike and person from the image.

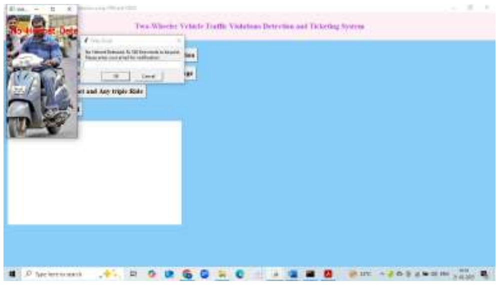

Fig: No helmet detection

Here helmet is not detected and we have been given option to enter email id for ticketing.

Once we enter email, we will receive email as below.

Fig: Performance of algorithm

Performance is showing with performance metrics.

Same will work for triple riding.

Fig: Triple riding n No helmet detected

Both two wheeler violations done.

CONCLUSION

In conclusion, the integration of automated helmet detection systems utilizing advanced technologies such as Convolutional Neural Networks (CNNs) and object detection algorithms like YOLO (You Only Look Once) has significantly enhanced traffic safety measures for motorcyclists. These systems effectively identify helmet usage violations in real-time, enabling prompt enforcement actions and contributing to a reduction in motorcycle-related injuries and fatalities. For instance, the implementation of an improved YOLOv5 detector, augmented with triplet attention mechanisms, has demonstrated notable improvements in the precision and recall rates of helmet detection tasks.

Moreover, the deployment of these automated systems streamlines the monitoring process, reducing the reliance on manual surveillance and allowing for more efficient allocation of law enforcement resources. By capturing essential data, such as license plate numbers, and issuing timely notifications to offenders, these systems ensure consistent enforcement of helmet laws. This technological advancement not only promotes a culture of compliance among motorcyclists but also provides valuable data for traffic management and policy-making, ultimately contributing to safer road environments.

REFERENCES

1.A. Bochkovskiy, C.-Y. Wang and H.-Y.

Mark Liao, "YOLOv4: Optimal speed and accuracy of object detection", *arXiv:2004.10934*, 2020.

2.N. Wojke, A. Bewley and D. Paulus, "Simple online and realtime tracking with a deep association metric", *Proc. IEEE Int. Conf. Image Process. (ICIP)*, pp. 3645-3649, Sep. 2017.

3.A. Bewley, Z. Ge, L. Ott, F. Ramos and B. Upcroft, "Simple online and realtime tracking", *Proc. IEEE Int. Conf. Image Process. (ICIP)*, pp. 3464-3468, Sep. 2016.

4. R. Smith, "An overview of the Tesseract OCR engine", *Proc. 9th Int. Conf. Document Anal. Recognit. (ICDAR)*, pp. 629-633, Sep. 2007.

5.A. Tonge, S. Chandak, R. Khiste, U. Khan and L. A. Bewoor, "Traffic rules violation detection using deep learning", *Proc. 4th Int. Conf. Electron. Commun. Aerosp. Technol. (ICECA)*, pp. 1250-1257, Nov. 2020.

6.J. Chiverton, "Helmet presence classification with motorcycle detection and tracking", *IET Intell. Transp. Syst.*, vol. 6, no. 3, pp. 259-269, 2012.

7. K. Dahiya, D. Singh and C. K. Mohan, "Automatic detection of bike-riders without helmet using surveillance videos in real-time", *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, pp. 3046-3051, Jul. 2016.

8. X. Wang, L.-M. Meng, B. Zhang, J. Lu and K.-L. Du, "A video-based traffic violation detection system", *Proc. Int. Conf. Mech. Sci. Electr. Eng. Comput. (MEC)*, pp. 1191-1194, Dec. 2013.

9. N. C. Mallela, R. Volety, R. P. Srinivasa and R. K. Nadesh, "Detection of the triple riding and speed violation on two-wheelers using deep learning algorithms", *Multimedia Tools Appl.*, vol. 80, no. 6, pp. 8175-8187, Mar. 2021.

10 B. Y. Reddy and M. Budka, "Detection of motor bicyclist violating traffic rules using computational neural networks".

11. V. Mandal and Y. Adu-Gyamfi, "Object detection and tracking algorithms for vehicle counting: A comparative analysis", *J. Big Data Anal. Transp.*, vol. 2, pp. 251-261, Nov. 2020.

12. S. Kumari, D. K. Gupta and R. M. Singh, "A novel methodology for vehicle number plate recognition using artificial neural network", *Proc. 3rd Int. Symp. Comput. Vis. Internet*, pp. 110-114, Sep. 2016.

13.H. Erdinc Kocer and K. Kursat Cevik, "Artificial neural networks based vehicle license plate recognition", *Proc. Comput. Sci.*, vol. 3, pp. 1033-1037, Jan. 2011.

14. J. Singh and B. Bhushan, "Real time Indian license plate detection using deep neural networks and optical character recognition using LSTM tesseract", *Proc. Int. Conf. Comput. Commun. Intell. Syst. (ICCCIS)*, pp. 347-352, Oct. 2019.