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Helmet Detection and License Plate Extraction

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Abstract: In recent years, there has been a significant surge in research targeting safety enforcement and traffic regulation automation, particularly focusing on helmet detection and license plate extraction. This paper presents a detailed survey of the myriad techniques and approaches that have been proposed and employed in the realms of helmet detection and license plate recognition. Starting with traditional image processing methods, we traverse through the evolution of methodologies, witnessing a shift towards sophisticated machine learning and deep learning models. For helmet detection, techniques range from color-based segmentation and Haar cascades to more advanced convolutional neural networks (CNNs). On the other hand, license plate extraction has seen innovations in methods such as edge detection, contour analysis, and region based CNNs. We discuss the merits, demerits, and performance metrics of each approach, giving readers a holistic view of the current state of the art and potential avenues for future research. Furthermore, the paper highlights datasets commonly used, challenges faced in real-world scenarios, and the integration of these technologies in smart city frameworks. The in-sights provided in this survey aim to guide researchers, practitioners, and policymakers in leveraging and refining these technologies for enhanced road safety and more efficient traffic regulation enforcement.

***Index Terms* – Helmet Detection, Machine Learning, License Plate Extraction**

I. INTRODUCTION

Traffic management in India faces substantial hurdles, with challenges stemming from dense populations, a surge in commuters, flawed infrastructure, and prevalent societal attitudes. Currently, many of India's city traffic systems are largely governed by manual supervision. This approach often results in significant con-gestion and errors, hindering effective traffic management and enforcement.

A report from 2019 by the Road Transport and Highways Ministry highlighted the concerning statistics: 37 percent of road accident victims were two-wheeler riders. A large fraction of these accidents was attributed to riders not wearing helmets. This violation alone accounted for almost 30 percent of the total road accident deaths that year. The World Health Organization further emphasized the importance of safety measures, stating that proper helmet use could drastically reduce fatalities and injuries. They also identified the dangers of mobile phone usage while driving, noting the increased risk of accidents. However, the challenge doesn't end with identifying the problems. The enforcement mechanism is overburdened. According to a 2017 report, there is an alarming mismatch between the number of automobiles on Indian roads (over 200 million) and the number of traffic police officers (less than 72,000). Due to this imbalance, it is difficult for the current systems to efficiently handle the variety of cars, variety of license plates, and constantly shifting traffic dynamics. Many cities continue to use antiquated traffic management systems that are unable to manage the volume of vehicles on the road today.

The necessity of technology intervention is highlighted by the inefficiencies in the current system. Adopting cutting-edge technologies is essential to addressing the changing issues of traffic management and violation control. Promising solutions can be found in automated systems, especially those that incorporate AI based on video. These devices have the power to revolutionize traffic surveil-lance, identify offenses and impose fines with accuracy, and support smooth enforcement.

Helmet detection systems basically use a combination of image processing and machine learning techniques to identify motorcycle riders wearing helmets. The very first step is to detect the motorcycle rider in the video frame or image. This can be done using YOLOv5 or by using the classification methods. The system can use various features once the rider has been detected such as the shape and color of the head and the presence of a helmet visor, to classify the rider as helmeted or non-helmeted.

Number plate extraction systems typically use a combination image processing and machine learning techniques to identify and extracting the number plate from video frame or an image. The first step is the detection of the number plate in the image or video frame. We can use various techniques such as Optical Character Recognition, Neural Networks etc. to extract the number and transform it into a readable form once the number plate from the image or video has been detected.

Even with the advancements in helmet detection and number plate extraction, certain issues remain that require attention. For example, helmet detection systems can be challenging in nighttime conditions and low light. Furthermore, when the number plate is covered in dirt, debris, or other things, number plate extraction devices may provide difficulties. In the following sections of this survey paper, we will review the state of the art in helmet detection and number plate extraction. We will discuss the various challenges that need to be addressed and the future directions of research in this field.

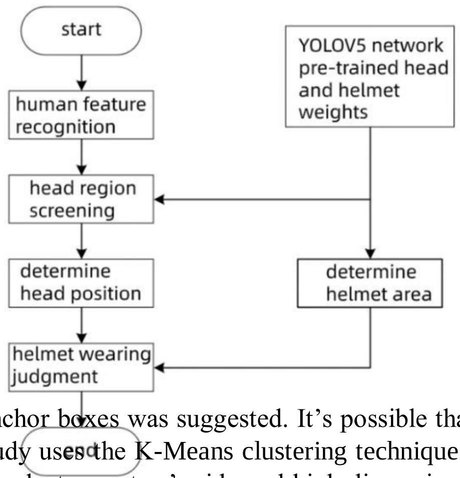
II. Literature Survey

2.1 HELMET Detection

Design and Implementation of Safety Helmet Detection System Based on YOLOv5

This paper [1] investigates one such method that uses an improved YOLOv5 (you only look once) model for helmet identification. The main duties performed by this approach are the adjustment of the initial candidate frame, loss function, and input size of the original YOLOV5 model. In order to enhance its suitability for helmet wearer identification, the YOLOV5 model has been improved. A camera and extra hardware are added to the learned model to form a complete real-time detection system.

High accuracy at real-time detection rates is guaranteed by the YOLOv5 identification model. YOLOV5 has a fast detection rate and good detection accuracy, but in order to create a better model that can better satisfy the requirements of real-time detection and yield a better detection result, we still need to optimize the original YOLOv5 and continually alter the super parameters.



In the paper, an improvement to create anchor boxes was suggested. It's possible that the generation ratio of the anchor box will directly affect the model's speed. This study uses the K-Means clustering technique to investigate the labeled target box's width inside the training set. Determine the nine cluster centers' wide and high dimensions, which correspond to the network profile's anchor parameter values. The Safety-Helmet-Wearing dataset clustering, an open-source dataset, serves as the foundation for the finest anchors. This is carried out in compliance with the YOLOV5 model network structure's characteristics.

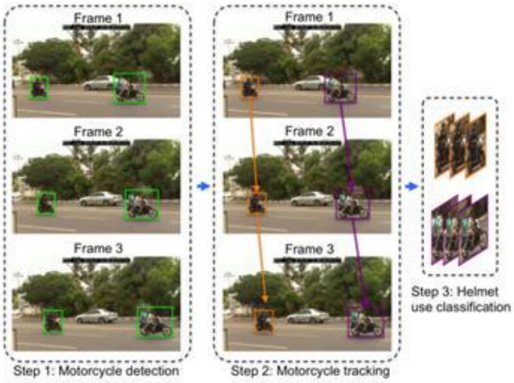
This type produces a high level of accuracy and precision. Additionally, the model generates findings quickly. However, because this model uses facial features to identify the region of interest, technical parameters like resolution and camera angle are crucial to its proper functioning.

Helmet Use Detection of Tracked Motorcycles Using CNN-Based Multi-Task Learning

This paper [2] addresses several of the shortcomings of current models, including their incapacity to monitor bikes over numerous frames and identify motorcycle riders from their passengers in order to inspect them for helmets. There are three main phases in the methodology that this paper discusses.

Motorcycle detection is the initial phase, and it may be accomplished in two ways: either using a single-stage model or a two-stage model. Because the two-stage model iterates through the picture twice rather than once, it is more accurate than the one-stage model but requires more computing power. Single stage models operate at a faster pace since they only go through the model once. In contrast to other common object identification models like YOLO, the authors of this research have chosen to employ a single stage method with a single-stage technique that is fine-tuned and pre-trained RetinaNet, which has a greater accuracy but a slower speed.

Based on the motion condition of the motorbikes and the visual resemblance of the vehicles across the frames, the second phase of this process is to track the matching motorcycles in neighboring frames. The detection of helmet wearing is the third and last phase. Once the car has escaped the camera's field of vision, this is done. Essentially, it employs a series of cropped photos taken of the car at various points along the track, which are combined to anticipate the helmet use case.



In the author's method, we must train CNNs for two reasons in addition to fine-tuning RetinaNet for motorbike identification. Visual similarity learning is one of them. In other words, if two picture patches are part of the same track, we want their distance to be short; if they are not, we want it to be large. The third goal of this is patch -based helmet use classification, which means that given a cropped picture patch, we want to predict the helmet use class (rider no, location, and helmet usage). Our method uses multi-task learning (MTL) which is basically used to learn both tasks simultaneously, saving time compared to training two independent CNNs.

A Swin Transformer-Based Approach for Motorcycle Helmet Detection

In this paper [3] the author addressed one of the main challenge of helmet detection that is distinguishing between passenger and the driver. The study of classical approaches in helmet detection has revealed a structured yet intricate process of identifying and classifying motorcycles and their riders. Typically, these methods leverage hand-crafted features extracted from images using descriptors like the Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), among others. The process generally follows a three-stage progression: back-ground subtraction for identifying moving vehicles, using collected foreground data to build a classifier to distinguish motorcycles from other entities, and finally, zeroing in on the rider's head as the Region of Interest (ROI) for helmet detection.

However, while these classical methods, as detailed in various studies have showcased promise, they are riddled with inherent limitations. The reliance on manually extracted features means that changes in lighting, view angles, or heavy traffic can compromise their efficiency. Furthermore, they necessitate calibration for each new scene due to restrictive dataset parameters. The limitations also extend to the inability to recognize multiple passengers on a motorcycle, focusing primarily on the rider. Consequently, while these methods may produce satisfactory results under controlled conditions, their adaptability and robustness in varied real-world scenarios remain questionable.

To distinguish between the passenger and driver the author proposed a model that is based on neural networks called as transformers. In this model for the purpose of feature extraction the author used the base most version of swin transformer and then combining this with Feature Pyramid Network with e Cascade Region-based Convolutional Neural Networks for the final detection. The preprocessing module consists of famous preprocessing and augmentation techniques that includes random resizing and random resizing including cropping. The pixel normalization is done by dividing the intensity of each pixel by 255.

2.2 Number Plate Extraction

License Plate Recognition System Based on Improved YOLOv5 and GRU

In this paper [4] the author proposed a license plate recognition system's framework that comprises two main components: license plate localization and recognition. This system integrates both parts through a data interface. The localization module utilizes an enhanced YOLOv5 model to first detect and crop license plates from images. Following this, the recognition network employs the GRU for sequence labeling and decoding. The resulting GRU matrix, paired with the ground-truth (GT) text, is processed through the CTC loss function. By evaluating the loss function values for each data point, the system derives the recognized license plate outcomes.

If we observe the license plate generally takes very small part in the image and two issues occur during detection of license plate. The information present in the detection area that is presented by the pixels is different which leads to poor detection of number plate and also during the training of the model labelling small objects can be affected by bias and the results will be greatly influence when there are small targets, and the classes are very large in number. To tackle the problems the YOLOv5 is improved by improving the feature extraction of model that would improve detection on small targets. Simultaneously the author proposed to use a single class model that would help in decreasing the parameters and thus by reducing the impact of label on detection and thereby resulting in increase in accuracy.

The recognition network is based on a gated recurrent unit (GRU) network, which is a type of recurrent neural network (RNN). RNNs are well-suited for sequential data processing, such as character recognition. The GRU network is trained to recognize the individual characters in a license plate image. The two networks are combined to create an end-to-end license plate recognition system. The detection network first detects the license plate in the image and outputs a bounding box around it. The recognition network is then applied to the cropped license plate image to recognize the individual characters. The recognition network uses a connectionist temporal classification (CTC) loss function. The CTC loss function allows the network to learn to recognize characters without the need for explicit character segmentation. This makes the recognition network more efficient and robust to noise and variations in the license plate image. The results prove that the combination of improved version of YOLOv5 and ated Recurrent Unit and Connectionist temporal classification has an accuracy of 98.98% and also meeting the requirements.

Research on Car License Plate Recognition Based on Improved YOLOv5m and LPRNet:

This research [5] proposes an enhanced YOLOv5m and LPRNet model-based automobile license plate identification technique. Based on an analysis of the YOLOv5m algorithm and the image features of the vehicle license plate, the algorithm is refined in three ways: the matching degree between the anchor frame and the detection target is enhanced via the K-means++ algorithm; the NMS method is refined via the DIOU loss function; and the feature map with 20 ×
20 is eliminated to decrease the number of detection layers. Without character segmentation, license plate character recognition is achieved using a lightweight LPRNet network. A license plate recognition system based on the IYOLOv5m-LPRNet model is built by combining the enhanced YOLOv5m algorithm with the LPRNet network. The authors suggested a few methods to increase license plate detection accuracy. The multidimensional clustering of label data sets using the K-means++ method can significantly shorten the time it takes the model to locate the anchor. Furthermore Given that NMS has a tendency to miss detection while screening the real target frame, the DIOU-NMS method is created by re-fining the post-processing technique of NMS using the concept of the DIOU loss function. The license plate in the traffic scenario is a tiny target, therefore fewer detection layers are needed. This means keeping the feature map of the scale with 20 × 20 and conserving the feature map of the scale with 80 × 80 and 40 × 40. In addition to satisfying license plate detection requirements, the enhanced network lowers network complexity and increases target detection and network running speeds. Plate identification is quicker and more accurate using this approach. For character recognition, it also makes use of a lightweight LPRNet network, which provides resilience and adaptability in challenging settings. A automobile license plate recognition system (IYOLOv5m-LPRNet model) is developed using this enhanced algorithm and LPRNet, and it is validated through rigorous training and simulations. Significant improvements in identification accuracy (99.49%), recall (98.79%), mAP (98.56%), and recognition speed (42 images per second) are demonstrated by the testing findings. The technique meets the requirements for complex license plate recognition with high accuracy, speed, resilience, and real-time performance.

Developing Learning-Based Preprocessing Methods for Detecting Com-plicated Vehicle License Plates

In this paper [6] the author proposed a system that can help extract the number plate in various scenarios. This method involves an enhanced preprocessing method that can help detect number plate in very complicated scenarios. Using techniques like mean shift detectors, this method also eliminates superfluous bounding boxes, which raises the false positive rate.

The process involves two main phases: model development and evaluation. In the model development phase, Support Vector Machine (SVM) and Extreme Learning Machine (ELM) algorithms are utilized independently for learning. Consistent pre-processing and extraction techniques are adopted for both these phases. During pre-processing, the Enhanced Contrast Histogram Equalization (ECHE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) methods are implemented. These techniques refine the challenging portions of vehicle images without degrading the quality of well-lit sections. In the feature extraction phase, Modified Histogram of Oriented Gradients (MHOG) and Local Binary Pattern (LBP) descriptors are handpicked due to their resilience under challenging conditions such as varying contrasts, dirt, low light, fog, and distortions. The detection phase then leverages the trained SVM and ELM models independently to pinpoint the License Plate (LP) areas in the provided vehicle images. The resulting detections are archived, setting the stage for a subsequent recognition process, completing a comprehensive Automatic Number Plate Recognition (ANPR) system.

III. CONCLUSION

In this paper we have explained how important it is to wear a helmet and how can wearing a helmet can prevent major accidents. We now know why it’s necessary to have a system that can recognize whether or not a person is wearing a helmet when riding a motorcycle.

In this paper we also reviewed various technologies and algorithms that mainly involve Deep Learning algorithms like CNN and YOLO which are useful to detect helmets in the given footage. We also have further seen on how we can isolate the number plate from the vehicle from the given footage using technologies like edge detection and algorithms such as Support Vector Machines etc. We have also seen that we can train an advanced Optical Character Recognition Model that can be used to extract characters from the image extracted.

Furthermore, we have also seen on how the proposed algorithms perform un-der given conditions and on how improving and custom training some algorithms improve the efficiency of model. We have also seen how to get better results, keeping efficiency and latency in first priority. As we can see that this work highly depends on efficiency and speed, so it is important to maintain them.

To summarize this paper provides the overview of the technologies used and methodologies proposed and how we can use them to help reduce the accidents that can occur by not wearing a helmet

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