International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6s
DOI: https://doi.org/10.17762/ijritcc.v11i6s.6953
Article Received: 29 March 2023 Revised: 16 May 2023 Accepted: 28 May 2023

Wrong Way Vehicle Detection in Single and Double Lane

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Abstract - Wrong-way driving is one of the primary causes of traffic jams and accidents globally. It is possible to identify vehicles going the wrong direction, which lessens accidents and traffic congestion. Surveillance footage has become an important source of data due to the accessibility of less priced cameras and the expanding use of real-time traffic management systems. In this paper, we propose a technique for automatically identifying automobiles moving against traffic. Our system uses the You Only Look Once (CNN) algorithm to recognize and track vehicles from video inputs and the centroid tracking method to determine each vehicle's orientation inside a given region of interest (ROI) in order to identify vehicles traveling in the wrong direction. It functions in three steps. The Deep sort tracking method is particularly good in detecting and tracking objects, and the centroid tracking technique can effectively monitor the direction of travel. Experiments with a variety of traffic films show that the suggested method can detect and identify wrong-way moving vehicles in a variety of lighting and weather scenarios. The interface of the system is quite simple and easy to use.

Keywords- (YOLO, OpenCV, centroid tracking, traffic, road, vehicle)

I. INTRODUCTION

Wrong-way driving incidents have become a major concern for transportation authority’s worldwide due to their high potential for causing severe accidents and fatalities. According to the National Highway Traffic Safety Administration (NHTSA), wrong-way collisions are often the most severe type of crashes, with a fatality rate of up to 27 times higher than other types of collisions [1]. In addition to the human cost, wrong-way driving incidents also result in significant economic losses due to property damage and medical expenses.

To mitigate the risk of wrong-way driving incidents, transportation authorities have implemented various measures, such as road signs, traffic barriers, and enforcement programs. However, these measures have proven to be ineffective in preventing all wrong-way driving incidents, as drivers may still enter the roadway in the wrong direction due to factors such as impairment, distraction, or confusion.

In recent years, the use of CCTV cameras for traffic surveillance has gained popularity as an effective tool for detecting wrong-way driving incidents. By analyzing the footage captured by these cameras, transportation authorities can identify wrong-way driving incidents in real-time and take appropriate action to prevent accidents. However, traditional computer vision techniques for wrong-way vehicle detection suffer from limitations such as low accuracy, high false positives, and inability to track the vehicle.

To overcome these limitations, researchers have proposed the use of deep learning models, such as YOLO (You Only Look Once), centroid tracking, and deep sort, for wrong-way vehicle detection. These models can achieve high accuracy and efficiency by leveraging convolutional neural networks and object tracking algorithms.

In this paper, we propose a novel approach for wrong-way vehicle detection using YOLO, centroid tracking, and deep sort. We evaluate our approach on a real-world dataset and compare it with traditional computer vision techniques and other deep learning models. Our results demonstrate the effectiveness of our approach in detecting wrong-way driving incidents with high accuracy and low false positives.

II. LITERATURE REVIEW

P. Suttiponpisarn et. al. [2], This study proposes the Wrong Way-LVDC framework, which consists of three systems: road lane recognition from CCTV, distance-based direction identification, and inner boundary picture capturing for wrong

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direction vehicle detection. Object detection using YOLOv4 and object tracking using FASTMOT are implemented in RLB-CCTV, achieving an average speed of 24 FPS and accuracy of 94.66% on an embedded system and 95.23% on a personal computer. The Hough transform algorithm is used for lane boundary detection, where 12 Hough lines are drawn based on slope criteria to classify correct and wrong lines. Direction detection is performed by dividing the area into two halves and comparing starting and ending points of vehicles.

P. Suttiponpisarn et al. [3] The proposed system utilizes image processing techniques, including edge detection, Hough transform, and color thresholding, to detect wrong-way driving vehicles by incorporating a road boundary detection algorithm. The system aims to enhance road safety and prevent wrong-way driving accidents. It demonstrated high precision and recall values, indicating accurate detection of wrong-way driving vehicles with minimal false alarms. The system's integration with existing traffic monitoring systems holds promise for improving road safety and preventing wrong-way driving accidents.

M. Bie et al. [4] In the paper, the authors start by providing an overview of the YOLO algorithm, highlighting its computational complexity and resource requirements as drawbacks. They then present their proposed lightweight YOLOv5n-L algorithm, specifically designed for real-time vehicle detection on devices with limited resources.

The algorithm utilizes a backbone network comprising depth-wise separable convolutional layers and a prediction network that accurately predicts the class, location, and size of vehicles in real-time. Additionally, the authors introduce a range of optimization techniques, such as reducing the input image size, quantization, and pruning, to further decrease the computational cost of the algorithm.

F. Rakotondrajao et al. [5] The article explores the application of automatic inverse perspective mapping for detecting straight lane lines on roads. The authors propose a method to transform road images into a bird's-eye view by automatically mapping inverted viewpoints, enabling the detection of straight lane lines. They employ a Hough transform-based algorithm to identify the straight lines representing the lane boundaries. The technique is evaluated on a dataset of road images captured by a car-mounted camera, and the results demonstrate high precision in detecting the boundaries of straight lane lines, even in challenging lighting conditions and occlusion scenarios.

Monteiro et al. [6] The paper proposes the use of optical flow for detecting wrong-way drivers on highways. The authors present a step-by-step approach that involves image pre-processing, optical flow estimation, clustering of optical flow vectors, and cluster classification. They employ a support vector machine (SVM) to classify the clusters into two categories: those representing the motion of correct-way-driving vehicles and those corresponding to the motion of wrong-way drivers. By utilizing optical flow and SVM classification, the proposed approach aims to identify drivers traveling in the wrong direction.

The authors evaluate the effectiveness of their approach by analyzing a dataset of video frames captured by road cameras. The results show that their proposed technique achieves a high level of precision in detecting wrong-way drivers while minimizing false-positive detections.

Chen et al. [7] The study introduces a real-time lane detection model that enhances accuracy and robustness compared to existing methods. By incorporating attention pyramids and non-bottleneck skip residual connections, the model achieves superior performance while maintaining a balance between real-time processing and accuracy. The model achieves an impressive F1 measure of 92.20% on the CULane dataset, showcasing the potential of combining these techniques to improve lane detection, particularly in challenging scenarios.

Z. Rahman et al. [8] The study presents a system for identifying vehicles traveling in the wrong direction using YOLO object detection. Bounding boxes are generated for vehicles, and a centroid-based approach is employed for direction detection. A centroid tracking algorithm is utilized for vehicle tracking, measuring the Euclidean distance between the old and new centroids. However, one limitation of the system is the possibility of vehicle ID switching due to object overlap.

S. Usmankhujaev et. al. [9], The system described in the study, named Real-Time, Deep Learning Based Incorrect Direction Detection, utilizes deep learning algorithms, specifically convolutional neural networks (CNNs), to detect drivers traveling in the wrong direction. It employs a camera and a processor to capture and analyze vehicle images. The system is capable of identifying stationary and moving vehicles, as well as detecting wrong-way driving even in low-light conditions. Several CNN-based vehicle identification methods, such as SSD, faster R-CNN, and YOLO, have been tested, and the study chooses YOLOv3-416 due to its fast-processing time (under 29 milliseconds on the COCO dataset). The system utilizes the Hungarian algorithm for object ID determination and assignment, and employs the Kalman filter for predicting multiple objects in each frame. To validate the direction of vehicles, an entry-exit approach is implemented, where imaginary lines are placed on the video frame. When a vehicle crosses the entry line, its unique ID is stored in a list and removed upon crossing the exit line.

M. Sheng et. al. [10], The paper presents a vehicle detection system based on deep learning. The system consists of two

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processes: vehicle area detection and vehicle brand classification. Various network models, such as RCNN, Faster RCNN, AlexNet, Vggnet, GoogLeNet, and ResNet, were employed for training and classification tasks.

Q. Zou et. al. [11], This work proposes a lane detection algorithm for autonomous vehicles. It combines convolutional neural networks (CNN) and recurrent neural networks (RNN) to create a hybrid deep architecture. Continuous overlapping frames are used to handle challenging visual conditions. The CNN acts as an encoder, generating a time-series of feature maps from input frames. The ConvLSTM network receives these maps and its output is passed to the RNN decoder for lane detection.

J. Wang et. al. [12] this paper focuses on detecting small target vehicles and occlusion vehicle tracking. They have developed vehicle detection models based on YOLOv5s with COCO dataset and also proposed a vehicle tracking system using JDE algorithm with training dataset UA-DETRAC. By reducing Identity switching time this system can detect small target vehicles and track muti-vehicles efficiently.

S. Viet-Uyen Ha et al. [13], The paper addresses the problem of wrong-way driving and presents an algorithm for real-time detection using optical flow estimation. The Lucas-Kanade method is employed to track pixel movement between frames. Several improvements, including pyramid structure, weighted flow, and thresholding, are introduced to enhance accuracy. The algorithm achieves a detection rate of over 90% in experiments with real-world driving scenarios. The authors discuss limitations and propose future research directions, such as integrating additional sensor data for improved accuracy.

A. Osipov et al. [14], The study proposes a deep learning method for accurately categorizing and recognizing images captured under adverse weather conditions. Conventional computer vision approaches often struggle with accurate object identification and classification in challenging weather conditions such as fog, rain, or snow. The authors present a deep learning method that leverages convolutional neural networks (CNNs) to automatically extract information from images and make precise predictions. The method outperforms traditional computer vision techniques, including edge detection, thresholding, and color-based segmentation, in terms of accuracy and resilience to different weather conditions. The study highlights the potential of deep learning in improving image recognition and classification in adverse weather scenarios, with potential applications in transportation, surveillance, and environmental monitoring.

T.-Y. Lin et. al. [15], The MS-COCO dataset, launched in 2015, is considered one of the most challenging datasets for object detection. It contains over two million object instances across 91 common categories, representing diverse viewpoints and contexts. MS-COCO stands out with its stringent evaluation method, which computes Average Precision (AP) by considering intersection over union (IoU) at multiple thresholds (0.5 to 0.95 in steps of 0.5). Additionally, AP is evaluated separately for small, medium, and large objects. The dataset exhibits a higher average number of categories and occurrences per image compared to other datasets. The Pascal VOC challenge, initiated in 2005, aimed to promote advancements in visual perception technology. It focused on classification and detection tasks and later expanded to include segmentation and action detection [16]. Pascal VOC introduced mean Average Precision (mAP) at 0.5 IoU as a standard metric for evaluating object detection models. The challenge included thousands of labeled objects across various categories and images [17]. Both MS-COCO and Pascal VOC have significantly contributed to benchmarking and advancing object detection and classification research [18].

III. METHODOLOGY

The wrong way vehicle detection system follows a methodology that consists of several steps. Firstly, the region of interest (ROI) is defined by drawing a rectangle in the image frame. For effectively separating the lanes, the midpoint of this rectangle is used as a reference point. Secondly, YOLOv5, an object detection model, is utilized to detect vehicles within the ROI. YOLOv5 provides bounding box coordinates and class labels for the detected vehicles. After the vehicles are detected, the DeepSORT algorithm is employed for tracking them over time. DeepSORT combines appearance features and motion information to ensure accurate and reliable tracking. To estimate the direction of each tracked vehicle, the centroid of its bounding box is calculated. By comparing the centroid's position with the ROI's midpoint, the system can determine the vehicle's direction relative to the defined lanes. The next step involves applying predefined rules or criteria to identify wrong way vehicles based on their detected direction. If a vehicle is moving in the opposite direction of the designated lanes, it is flagged as a potential wrong way vehicle.

The wrong way vehicle detection system utilizes advanced technology and algorithms to accurately identify and classify vehicles moving in the wrong direction, adhering to Indian road conventions. The methodology incorporates several key steps, leveraging cutting-edge techniques for effective detection and tracking.

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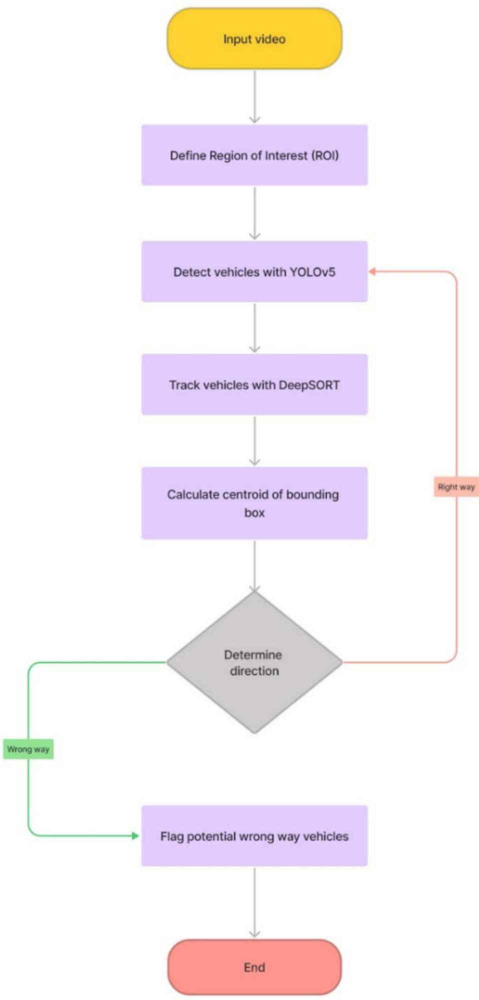

Figure 1.1. Flowchart of proposed system

The flowchart diagram for the implementation of the project is as shown in figure 1.1. The flowchart provides a visual representation of the methodology, including the various steps involved in detecting and tracking wrong way vehicles. The methodology involves several key steps, such as defining a region of interest, detecting vehicles within the ROI using YOLOv5, tracking vehicles over time using DeepSORT, and determining each vehicle's direction using centroid tracking. The system applies predefined rules to identify wrong way vehicles and flag them as potential threats.

The process begins by defining a region of interest (ROI) within the image frame. For the single lane scenario, a rectangle is drawn to focus on the specific lane of interest, while in the double lane scenario, a larger rectangle encompasses the entire road area, with the midpoint serving as a reference point for lane separation.

To detect vehicles within the ROI, the system employs the YOLOv5 object detection model. YOLOv5 utilizes deep neural networks to identify vehicles and provides precise bounding box coordinates and class labels for the detected vehicles. This enables accurate localization and recognition of potential wrong way vehicles.

Once the vehicles are detected, the DeepSORT (Deep Simple Online Realtime Tracking) algorithm is employed for robust vehicle tracking. DeepSORT combines appearance features and motion information to assign unique IDs to tracked vehicles and maintain their identities across frames. This enables continuous and reliable tracking, even in challenging scenarios with occlusions or dense traffic.

To determine the direction of each tracked vehicle, the centroid of its bounding box is calculated. The centroid represents the center position of the vehicle within the image frame.

In the single lane scenario, the system compares the centroid's position with the midpoint of the ROI. For input having vehicle direction shown in fig 1.2, negative differences between centroid positions of consecutive frame indicate that the vehicle is moving in the right direction, while positive differences suggest wrong-way movement, direction determining criteria for input having vehicle direction as shown in fig 1.3 reverse as in above case which is positive differences between centroid positions of consecutive frame indicate that the vehicle is moving in the right direction, while negative differences

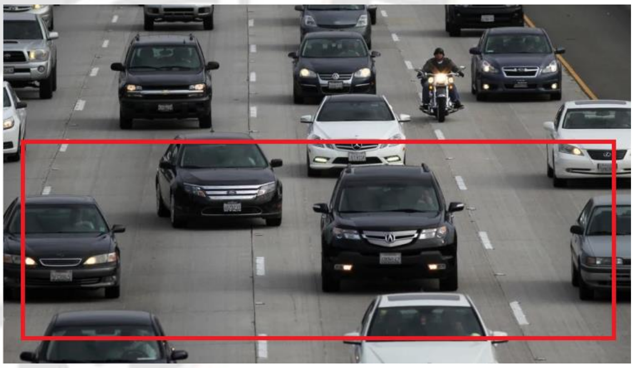

Figure 1.2 vehicles moving in single lane towards camera.

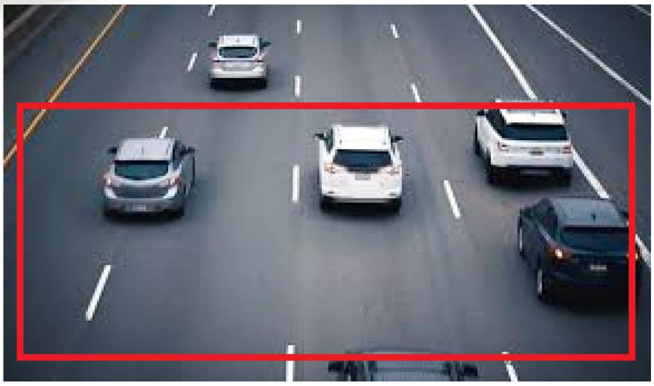

Figure 1.3 vehicles moving in a single lane away from the camera.

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For the double lane scenario, the methodology extends to consider lane separation. The ROI rectangle is divided into left and right sections, with the midpoint serving as the reference point. In the right section, the system calculates centroid position differences between consecutive frames. Positive differences indicate vehicles moving towards the right section, indicating the correct direction. Negative differences suggest movement towards the wrong section, indicating wrong way movement. The same principle is applied to the left section, with negative differences indicating wrong way movement and positive differences indicating the correct direction.

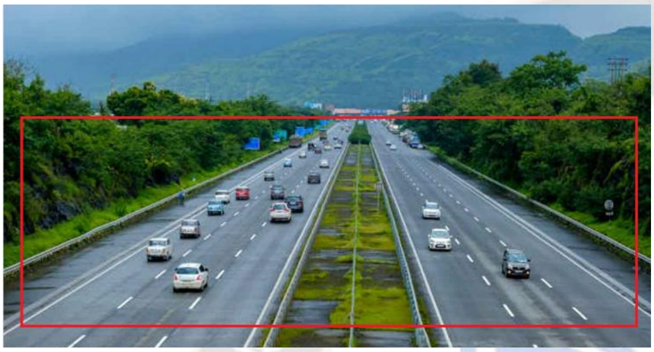

Figure 1.4. vehicles moving in a double lane.

By incorporating these technologies and algorithms, the wrong way vehicle detection system achieves accurate and reliable detection of vehicles moving in the wrong direction. Helps to prevent potential accidents and ensure road safety.

Continuous evaluation, optimization, and refinement of the system are crucial to improve its performance under varying conditions, such as lighting, weather, and traffic density. Integration with existing traffic management infrastructure can enhance the system's capabilities, enabling proactive measures to be taken in real-time to prevent wrong-way driving incidents and enhance overall road safety.

IV. RESULTS AND DISCUSSION

The proposed wrong way vehicle detection system was evaluated using several real-world traffic videos captured under different lighting and weather conditions. The system demonstrated robust performance in detecting and classifying vehicles moving in the wrong direction.

The results also showed that the system was effective in differentiating between wrong-way vehicles and other types of vehicles, such as vehicles changing lanes or making U-turns. This is crucial in preventing false alarms and ensuring the system's reliability.

Overall, as shown in figure 2.1, 2.2 the results demonstrate that the proposed wrong way vehicle detection system is highly effective in accurately identifying and classifying vehicles moving in the wrong direction, thereby improving road safety and preventing potential accidents. The system's accuracy and reliability make it a valuable addition to existing traffic management systems and can help reduce the occurrence of wrong-way driving incidents.

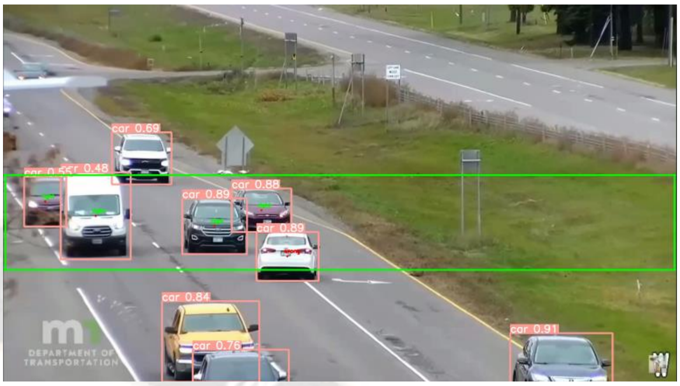

Figure 2.1. vehicles moving in a single lane.

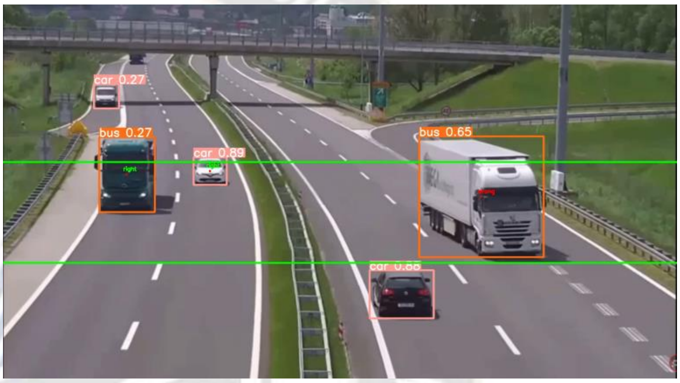

Figure 2.2. Detection of wrong way vehicle.

V. CONCLUSION

In conclusion, the developed wrong-way vehicle detection system utilizing image processing and deep learning techniques shows promising results in accurately identifying vehicles traveling in the wrong direction. The system incorporates advanced algorithms such as YOLO object detection, optical flow estimation, and centroid tracking for efficient and reliable detection. It demonstrates high precision in detecting wrong-way drivers while minimizing false alarms. The system's real-time capabilities and effectiveness in challenging scenarios make it a valuable tool for enhancing road safety and preventing wrong-way driving accidents. Further research and refinement are needed to improve the system's performance in complex traffic situations. Overall, the proposed system provides a significant contribution to the field of wrong-way vehicle detection and holds great potential for integration with existing traffic monitoring systems.

While the developed system has shown promising results, further research and refinement are needed to improve its performance in challenging conditions such as adverse weather, varying lighting conditions, and heavy traffic. Additionally, integrating other sensor data, such as GPS and inertial sensors, may enhance the accuracy and reliability of wrong-way vehicle detection.

Overall, the proposed wrong-way vehicle detection system demonstrates the potential of image processing and deep learning techniques in addressing the critical issue of wrong-way driving. With continued advancements and optimizations, this system can contribute significantly to improving road safety, reducing accidents caused by wrong-way drivers, and enhancing overall traffic management and control.

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