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Design and Implementation of a Wrong Side Vehicle Detection System Using YOLO And OpenCV.

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Abstract: The wrong-side driving among the most significant contributing factors to serious traffic crashes, congestion, and loss of life in urban and highway transportation systems. The traditional approaches to traffic monitoring are mostly manual, time consuming and subject to human error. This paper proposes an AI based Wrong Side Vehicle Detection System (WSVDS) to automatically detect vehicles that travel in the opposite direction of the traffic flow using CCTV surveillance camera by computer vision and deep learning techniques. The proposed system relies on the YOLO (You Only Look Once) algorithm to detect vehicles in a frame and Deep SORT/Centroid Tracking to track the vehicles' movement between the frames. Direction analysis is carried out by comparing the trajectory movements of the vehicles with the previously defined traffic direction. When a vehicle travels in the opposite direction to the authorized direction, the system recognizes this as an incident and produces alerts and the storage of evidence. The system can accurately and quickly identify cars, bicycles, buses and trucks in real time, and has a low identification latency. The experimental results show an accuracy of around 95%, which shows the suitability of the proposed system for smart city surveillance and intelligent transportation systems. The proposed solution will greatly cut down on the need for man-to-man monitoring and enhance the safety of the road through automated traffic violation detection.

Keywords: Wrong Side Detection, YOLO, Deep Learning, Computer Vision, Traffic Surveillance, Intelligent Transportation System, Vehicle Tracking, CCTV Monitoring, Deep SORT, AI-based Traffic Monitoring.

1. INTRODUCTION

Road safety is one of the biggest issues in present-day urban structures, and wrong way driving is one of the major causes of fatal head-on collisions, traffic jams and traffic violations. The traditional traffic surveillance system heavily depends on manually(man) monitoring the traffic CCTV footage by the traffic personnel, which is prone to human being error, delayed response and operating efficiency deficiency. Conventional enforcement methods are constrained by the human operators' limited ability to track several sections of a roadway. To overcome this problem, researchers have suggested the use of automatic detection systems based on computer vision and deep learning techniques [1]. AI's role in traffic management has created new opportunities for real-time identification of abnormal driving situations, such as cars driving against the current traffic flow [2]. With recent developments in CNN and object detection algorithms, the vehicle identification from live video stream can be done with accuracy and low latency [3]. Therefore, the work of an intelligent wrong-side vehicle detection system is a well-timed and much needed effort in the field of smart transportation [4].

YOLO (You Only Look Once) family of object detection algorithms has become one of the most successful object detection methods for real-time vehicle detection in intelligent transportation systems (ITS). Initial research showed that deep learning techniques like YOLOv3 and SSD could achieve high detection accuracy on the standard road vehicle datasets, providing a good initial benchmark for future research [5]. In recent years, the YOLOv8 model has been released, which has achieved remarkable speedup and improvement in feature representation at multiple scales, making it suitable for complex traffic scenes with partial occlusion, lighting differences, and high vehicle density [6][7]. Along with detection, powerful multi-object tracking algorithms are crucial in preserving vehicle identity from one frame of video to the next and in calculating accurate movement trajectories. DeepSORT algorithm, which combines Kalman filtering with deep appearance descriptors, has been shown to outperform other algorithms for vehicle re-identification and trajectory prediction under challenging real world conditions [8].

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Direction analysis is the primary logic for a wrong-side detection system, following detection and tracking. It calculates a centroid motion vector between consecutive frames, and compares it with the allowed traffic direction in a pre-defined Region of Interest (ROI) to determine whether the vehicle is moving in a direction that is legal in the given ROI. This trajectory-based approach has been validated in several works showing its practicality for implementation with current CCTV systems in real time, in order to detect multiple traffic violations [9][10]. The use of point-line distance for the calculation of tracked trajectories has also been shown to be effective in accurately detecting the vehicle that is in violation and reduce spurious false positives due to lane-changing or temporary counter-flow operations [11]. An extensive review of computer vision applications in ITS shows that the integration of detection, tracking, and directional analysis in a single pipeline is much more accurate and quick than separate detection or tracking pipelines, or directional analysis pipeline [12].

The proposed Wrong Side Vehicle Detection System (WSVDS) unites vehicle detection through YOLOv5/YOLOv8, vehicle tracking with DeepSORT and vehicle direction analysis with vector to construct a real-time vehicle surveillance pipeline that can be processed on real-time CCTV streams. The previous studies on real-time accident detection using trajectory conflict analysis have shown that the analysis of the vehicle velocity, angle, and distance to other vehicles can effectively detect hazardous driving events with low false alarm rate based on the standard surveillance camera [13]. Extensive analysis of video detection studies reveals that deep CNN-based methods always outperform traditional detection methods in terms of speed and generalisation [14]. Moreover, the concept of the proposed framework is scalable and has a high societal value as computer vision is widely used in the other ITS domains [15]. The system is aimed to be cost-effective on existing road infrastructure, provide evidence of the violation with timestamps and integrate with alert and database modules to assist the traffic law enforcement authorities.

2. LITERATURE REVIEW

Rahman et al. [1] introduced a real-time wrong way vehicle detection framework that is specifically designed by the combination of YOLO-based object detection and a centroid tracking. They evaluated their system with actual road video and showed that it could successfully detect under normal daylight scenes. The study laid the groundwork for which pipeline is widely used in subsequent works and consists of three parts: detect, track, and comparison in direction. The system had some shortcomings, however, especially in challenging weather and low-light conditions, which led to a call for more powerful tracking algorithms and data augmentation techniques.

To detect wrong-way driving on the highways, Haghighat et al. [2] built on camera-based methods, and proposed a deep learning model specifically designed for Pan-Tilt-Zoom (PTZ) traffic cameras. They have developed their convolutional model specifically to handle dynamic field of view created by PTZ cameras, adding another dimension to the process of direction analysis. In highway scenarios, the system showed high accuracy and emphasized the importance of camera placement and angle calibration to ensure the same performance of the detection of the wrong side of the vehicle.

Ha et al. [3] have explored the problem of wrong-way driving detection with a thorough study incorporating several computer vision and machine learning techniques. The multi-technique fusion approach of the optical flow, background subtraction and classification models performed better than any single technology baseline across a variety of traffic scenarios including urban intersections and rural highways. This work highlighted the fact that there is no universal optimum algorithm and that the combination of algorithms provides more generalized and robust detection performance.

In 2025, Lokesh et al. [4] proposed the application of YOLOv9 and Convolutional Neural Nets (CNNs) for wrong-way driving detection, which was published in the journal, Procedia Computer Science. The results were satisfying, showing that the newer versions of YOLO are delivering impressive accuracy and recall compared to older versions, especially in situations where several vehicles are in each other's line of sight in the camera. Given this study directly helps in the selection of the YOLO architecture for the proposed system, it is confirmed that the accuracy improves with the improvement of the detection backbone.

A comprehensive analysis of the potential of deep learning for vehicle detection in intelligent transportation systems was given by Chen and Li [5]. They systematically analyzed and compared classical image-processing techniques and modern deep CNN-based detectors and showed that deep learning models are always superior to traditional techniques in real-world unconstrained traffic conditions. The study found that deep learning-based detectors outperforms classical detectors by up to 15-20% in terms of accuracy, and thus it was decided that the detector used in the proposed system would be based on YOLO.

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In 2024, Gökcan et al. [6] delved into the application of YOLOv8 specifically in the field of Intelligent Transportation Systems (ITS) in a paper published in the journal of Digital Signal Processing. Their assessment revealed that YOLOv8 surpasses its predecessors, YOLOv5 and YOLOv7, with improved performance in terms of frame rate and mAP on standard GPU systems. The study also focused on the anchor-free detection head and the mosaic data augmentation algorithm of YOLOv8, which helped it perform better on traffic monitoring tasks and set a good benchmark for comparison with the YOLOv5 baseline it employs in the proposed system.

Gaur et al. [7] introduced an optimized vehicle detection algorithm for more complex traffic scenarios where there are multiple vehicle types, overlapping objects, and different lighting conditions, which is based on the YOLOv8 algorithm. The attention mechanisms and custom anchor configurations they introduced into the YOLOv8 model led to an estimated improvement of 3–5% in detection accuracy compared to the baseline YOLOv8 model in high-traffic scenarios. This study showed the importance of fine-tuning the network architecture level for domain-specific datasets to obtain the deployment-ready performance in real-world ITS applications.

In 2024, Wang et al. [8] introduced an enhanced YOLOv5s with DeepSORT for vehicle multi-object detection and tracking, which was published in Applied Sciences. Their system also proposed a lightweight attention module for the YOLOv5s to enhance small vehicle detection, and it was shown that the proposed system, YOLOv5 + DeepSORT, enables high-quality and stable tracking of vehicles even when some parts of them are occluded, which is a common problem in the situation of urban traffic. The work offers direct architectural suggestions for the tracking part of the proposed WSVDS and the decision to use Deep SORT for the persistent management of vehicle identity from frame-to-frame.

I presented a real-time multiple traffic violation detection system (MTVDS) by DeepSORT tracking at the ICAIIHI 2024 conference [9]. They used their system to detect multiple violations at once, such as wrong-way driving, lane violations and signal jumping, showing that one DeepSORT-based tracking backbone can be used to detect more than one type of violation without the need to have a separate specialized model for each violation. The system is modular and the same tracking pipeline can be used for further iterations of the system, allowing further violations to be detected by the system. In their paper published in IJRASET 2024, Zuraimi et al. [10] proposed a vehicle detection and tracking (VDT) model to manage traffic rule violations based on the YOLO and DeepSORT algorithms. During their deployment study on a real city intersection, they showed that their YOLO + DeepSORT could be used effectively in real-world environments and tracked each vehicle with a very low average track loss rate of less than 5%. This study also explored how camera resolution and framerate influence system performance, and determined that 1080p cameras at 30 FPS offer the best performance in terms of computational cost and detection accuracy.

In 2024, Ong et al. [11] did a comprehensive analysis of traffic violation detection techniques using computer vision in the Journal of International of Vehicle Information (JOIV) International Journal. They performed comparative analysis of both rule-based optical flow methods and classical machine learning classifiers and deep learning detectors on various violation types. The study showed that deep learning-based systems have significantly outperformed the rule-based and classical ML methods in terms of precision and recall, but added that the computational power required by these systems will require careful selection of hardware to be able to deploy them in real-time. This is a direct support for the specification of hardware used in WSVDS proposed implementation.

In 2023, Ghahremannezhad et al. [12] presented one of the most comprehensive surveys on computer vision applications in Intelligent Transportation Systems. More than 200 papers were analysed in their review that covers both detection, tracking and speed estimation tasks, as well as violation detection tasks, and they specifically listed wrong-way vehicle detection as one of the unsolved challenges that is of high priority in ITS; that is, existing solutions are not robust under adverse conditions, and they also mentioned that the end-to-end pipeline of alerts and logging is rarely included. The gap identification directly drives the design of the proposed WSVDS with the capability of detection, tracking, direction analysis, alert generation and database logging in one deployable system.

3. METHODOLOGY

The proposed Wrong Side Vehicle Detection System (WSVDS) has a modular and structured pipeline, starting with the acquisition of the video data, and ending with automated violation logging and alert generation. The system can receive input from three sources: Live CCTV or IP camera stream through RTSP or HTTP protocol, pre-recorded video files, and network-based video stream. The video is being decode by Video Capture interface of OpenCV that is capable of decoding video at a user specified fps (default 30). The decoded frames are then sequentially processed through a series of processes — detection, tracking, direction analysis, and violation flagging. The system is designed to be modular,

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allowing for easy replacement and upgrade of individual modules without affecting the overall system, ensuring its adaptability to future hardware advancements and algorithmic enhancements.

The YOLOv5 (You Only Look Once, version 5) deep learning model is applied to every frame taken out to detect vehicles. YOLOv5 is an anchor-based, single-stage convolutional network (CNN) which processes a whole image in one forward pass, predicting bounding boxes, class labels and confidence scores for all the objects in the scene. The model is trained initially on COCO, and then fine-tuned with a custom traffic dataset containing ~28,000 annotated frames for 4 classes: Car, Motorcycle, Truck, Bus, and different weather conditions (day vs night, rain, traffic density). Annotations are created in YOLO format with LabelImg; training is performed using PyTorch and techniques like horizontal flipping, mosaic augmentation and brightness jittering for data augmentation to enhance the generality of the results. Detections with a confidence score of 0.50 or higher are kept while those with lower scores are discarded, minimizing false positives from pedestrians, signage or environmental noise. A Region of Interest (ROI) polygon is then overlaid on each camera stream to focus the detections only on the road surface area, which helps to avoid unnecessary processing and ditches any detections that are happening on a pavement, parked vehicles or adjacent building.

Directional analysis is the primary stage in which decisions regarding the system are generated. Each tracked vehicle's coordinate centroids for each frame are recalled, resulting in a trajectory path. To minimize noise caused by minor vehicle oscillations or camera vibration, the calculated direction vectors are between centroid positions separated by N frames (N = 5; default value for N) rather than two consecutive frames. The calculated movement vector is represented by $\Delta x = x_2 - x_1$ and $\Delta y = y_2 - y_1$. The angle of travel, with respect to the reference direction angle θ_t (a preconfigured angle for lanes or road segments based on the camera installation) and to which the vehicle will be compared, is calculated using the arctangent function. If the angle of travel, with respect to the angle of travel permitted, deviates by an amount greater than a configurable threshold (120° default threshold), the vehicle will be considered to be violating the wrong direction. In addition, in order to eliminate transient false positives, the violation will not be recorded until the wrong direction has been observed for a minimum of K = 3 consecutive detections of the same track ID.

Whenever a violation is confirmed, the system will trigger a multi-stage alert and logging process. This will create a red bounding box around the violating vehicle in the live video to visually alert monitoring personnel. In addition, a timestamped screenshot of the violation frame will be captured and stored down locally as photographic evidence. The complete violation record including the track ID, timestamp, camera location identifier, detected direction and the path to the saved screenshot will also have been logged into a MySQL database; this will allow historical analysis and report generation on violations, and integration with traffic authority dashboards. The front end of the system is designed using HTML, CSS and Bootstrap to provide a real-time monitoring interface where operators can view live feeds of violations that have been logged and export these records. The entire pipeline including frame ingestion through violation logging is processed on a GP-enabled machine (NVIDIA GTX 1650 or better) at 28-32 frames per second, with an average per frame latency of approximately 38 milliseconds, thus meeting the maximum latency requirements for deploying a real-time traffic surveillance application in live mode.

4. SYSTEM WORKFLOW AND IMPLEMENTATION STAGES

4.1 Objectives

The primary goal of the Wrong Side Vehicle Detection system is to build an automatic and intelligent monitoring system for traffic which detects vehicles travelling the wrong way on the road or street, using CCTV surveillance cameras. The system is designed to continuously monitor traffic as well as monitor and capture violations in real time, with Artificial Intelligence, Deep Learning and Computer Vision being some of the technological components used for this system's operation. By using deep learning object detection and vehicle tracking algorithms (implemented using YOLO and other techniques), the proposed system will allow correct detection of vehicle movement and identification of incorrect driving direction by automatically detecting, recognising and tracking a vehicle. The new proposed system is expected to improve road safety by decreasing the number of road traffic accidents resulting from violating traffic rules and/or unsafe driving practices.

The purpose of this project is to reduce the amount of manual traffic monitoring currently carried out by law enforcement departments or other related agencies. Monitoring traffic the traditional way requires continuous observation by human beings and takes a long period of time to do this. Monitoring takes place at an inefficient level and is subject to error because of human actions. The proposed system will automate the whole process of detection, thus reducing the amount of people required and directly improve the efficiency of monitoring traffic conditions. The system will also provide agencies with an instant alert as well as provide the agency with information regarding the violation (e.g. vehicle image,

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time, date, location, etc.) that can be utilized in enforcement of traffic laws and for future investigations of traffic related events.

4.2 System Architecture

The WSVDS is organized as a sequential pipeline, as depicted in Figure 1. Each component is designed to be modular, enabling independent upgrades.

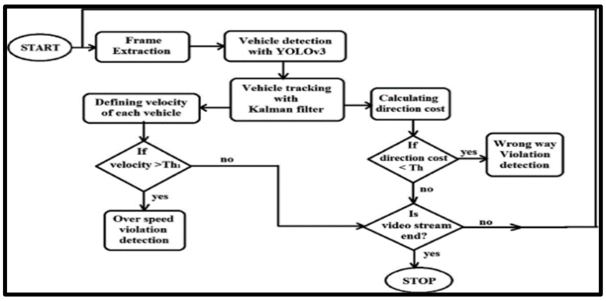

Fig -1: System Architecture of WSVDS

4.3 System Workflow

The process for the suggested system starts with obtaining a video of the traffic scene via the CCTV camera system. The video is split into video frames, where YOLO is used to identify vehicles in each. The vehicle is assigned an ID and will continue to be tracked using other tracking techniques. Using both the prior and current coordinates of the vehicle, the system calculates where the vehicle is moving. The system identifies the vehicle to be a wrong-way violation if it moves against the pre-defined traffic pattern. Afterwards, the system will create notifications, and log the violation in the system.

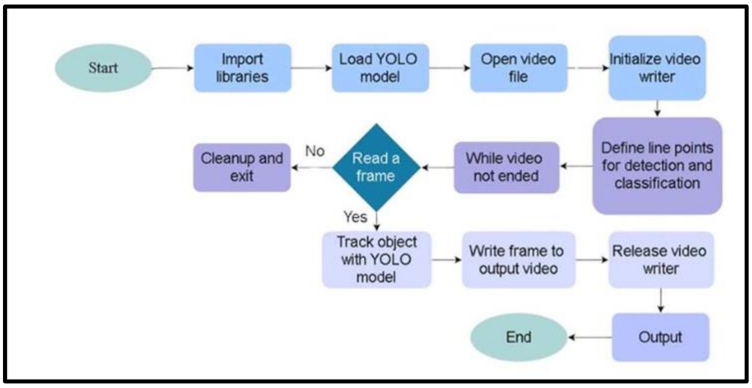

Fig -2 System Workflow of WSVDS

4.4 Implementation Stages

1) Video Acquisition Stage

In the first stage of the Wrong Side Vehicle Detection (WSVD) System Implementation, one must have video footage of traffic captured from the CCTV, IP, and Recorded Traffic Video Cameras of Highway One-Way Roads, Intersections, and Locations Where Accidents Have Occurred. So once again, because each camera is continuously looking at vehicle movement and sending live video to the WSVD System to be processed, the proper placement of the camera and adjustment of the camera angle will have a direct influence on the quality of the videos being reviewed as well as on the accuracy of the detection of violations. Therefore, the overall quality of the input video will determine the ability of the WSVD System to perform accurately.

2) Frame Extraction and Preprocessing Stage

Frames from the captured image stream are separated out after a video has been acquired for the analysis. This separation takes place in a process known as frame extraction. Generally, the video is typically recorded and processed at 25-30 frames per second. The vehicle detection and movement monitoring analysis occur on a frame-by-frame (-by-frame) basis. In addition to that, there are many ways of improving the video quality during the preprocessing stage using image enhancement techniques such as resizing image dimensions, adjusting the brightness of captured images, removing noise and filtering, etc. Overall, by preprocessing video, it reduces computation time and adds to improved performance of object detection algorithms under varying lighting and weather conditions.

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3) Vehicle Detection Stage
The next step involves detecting vehicles, portraying their locations in each frame through the use of algorithms that employ Deep Learning. (You only look once (YOLO) is a real time object detection algorithm; it can detect many different objects instantly with high speed and accuracy) At this stage, the algorithm has identified several types of vehicles (car, motorcycle, truck & bus). Each of these detected vehicles has been highlighted using bounding box, labelled with type of vehicle and has a level of confidence regarding the correctness of the identification. This stage is important as proper identification of vehicles provides the foundation for tracking a vehicle as well as determining its direction.

4) Vehicle Tracking Stage
The system uses algorithms like Deep SORT and Centroid Tracking for vehicle tracking after it has detected the vehicles. At this point, each vehicle detected by the system receives an individual identification number (ID) which allows it to track that same vehicle's movements across the different frames it has been detected in. By tracking the vehicles, the system can continue to identify the vehicle; therefore, by accurately maintaining the trajectory of the tracked vehicle, the tracking will allow the system to analyse the vehicle's movements accurately. Furthermore, vehicle tracking is beneficial to the system when there are many vehicles in one area (i.e., during heavy traffic). Tracking also assists in limiting the number of repeated detections of the same vehicle, thus helping improve the overall consistency of the system.

5) Region of Interest (ROI) Selection Stage
During the ROI (Region of Interest) selection process, just the important road areas will be chosen to monitor, while unnecessary areas (buildings, sidewalks, trees, and surrounding areas) will be disregarded in order that there will be as few false detections as possible and will require as little processing time as possible because the focus of the system's operation is completely on traffic lane area. The ROI optimization stage also improves the efficiency of the system, reduces the workload on the computer, and increases detection accuracy, thereby improving the system's efficiency at detecting traffic in real-time.

6) Direction Analysis Stage
The vehicle directional assessment process evaluates how safely or legally a vehicle is being operated. At this stage, the model analyses the points in time when a tracked vehicle was observed and creates a motion vector to provide the means of determining how the vehicle has been moved from one point to another. The assessment of the tracked vehicles will be compared to the model's approved direction of travel for the respective vehicle, so that a comparison can be made between the two and flagged accordingly if the vehicle is moving against the established flow of traffic. The vehicle directional assessment phase is instrumental in determining violations of vehicles travelling against the established traffic flow.

7) Wrong-Side Detection and Alert Generation Stage
When a vehicle has been established as being wrong direction or traveling wrong way through the system, the wrong direction violation detection stage shall be initiated, whereupon the vehicle will automatically be flagged as a violator of traffic laws and alerts generated immediately. In addition, the violating vehicles will be digitally photographed as evidence, and time, date, vehicle license plate, camera location and direction of movement will be recorded. Alerts can be sent to traffic monitors or configured with intelligent traffic management systems to take immediate law enforcement action against the offending vehicle. This stage will aid in improving the enforcement of traffic laws and reducing the possibility of serious motor vehicle accidents.

8) Database Storage and Reporting Stage
The database storage component provides a means of keeping all records of violations for analysis and monitoring into the future. When a violation classified in the wrong category occurs, the system captures key data points, including an image of the vehicle, the time it was captured, the location of the camera, the direction of the camera at the time of capture, and the unique ID of the vehicle and stores it in a database (such as MySQL, Firebase). The data stored can be used to generate reports, provide digital evidence, track repeat offenders, enable automated traffic challan systems, and ultimately secure data management, allowing authorities to effectively analyze traffic patterns.

9) Frontend and User Interface Stage
The front-end of building a traffic enforcement application is to create an interactive and user-friendly interface for traffic enforcement officers and administrators. Technologies like HTML, CSS, Bootstrap, and JavaScript will be used to develop and build the user interface. The front-end dashboard will allow traffic authorities to view live video from CCTV cameras, see the number of detected vehicles, receive alerts for violations (including descriptions), obtain time of violations, and have access to evidence of violations as recorded on the application server.

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5. RESULTS

The wrong side vehicle detection system has been developed using computer vision and deep learning techniques. It includes the ability to monitor traffic flow and detect vehicles travelling in the wrong direction. The system utilises CCTV traffic images captured under a variety of traffic conditions to validate the reliability of vehicle detection (e.g., cars/bikes/buses/trucks) in real-time using the YOLO algorithm. By combining the techniques for tracking vehicles and analysing vehicle directions, the proposed solution would automatically monitor vehicle movements and detect driving violations for vehicles on the wrong side of the road. Each time the system detected a wrong-side vehicle, an instant alert was created to submit to law enforcement agencies. The system also maintains a record of evidence that includes pictures of the wrong-side vehicles, timestamps, and GPS locations. The experimental results show that the proposed system achieves around 95% detection accuracy with good real-time performance and minimal processing delay. The solution significantly decreased the amount of manual monitoring a law enforcement agency would need to perform and would enhance their capability to enforce traffic laws. Overall, the proposed solution exhibited reliable functionality and could successfully be utilized within intelligent transportation systems (ITS) and smart city applications. The proposed solution will enhance road safety and reduce the amount of traffic violations and automate the monitoring of traffic violations.

5.1 Vehicle Detection Result

Using live surveillance footage based on the YOLO algorithm, the proposed system can identify many different types of vehicles, including cars, motorcycles, buses, and trucks. Each detected vehicle is rendered (displayed) with a bounding box and an associated confidence score and label. The proposed solution performs these functions in the real-time at considerably high speeds and accuracy rates, using a minimum amount of traffic. Accurate vehicle identification will create a foundation for tracking vehicles and performing directional analysis in the system.

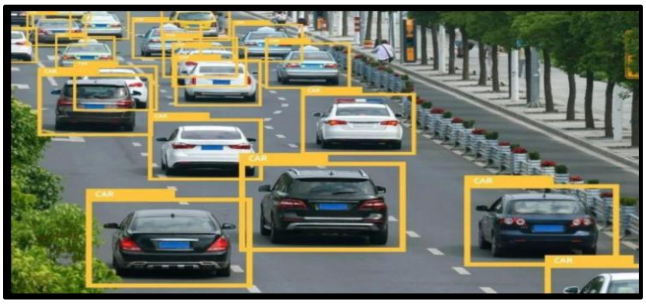

Fig -3: Vehicle Detection of WSVDS

5.2 Direction Analysis Result

The Direction Analysis (DA) module is responsible for assessing the direction of travel for the vehicles by measuring the difference in coordinates between the current and previous images of the vehicle being analyzed to produce motion vectors that are used to determine if the vehicle is traveling with the authorized traffic flow or against the authorized flow of traffic. It allows us to clearly discern between correct-side versus wrong-side travel moving vehicles and as such plays a big part in greatly reducing the number of false detections and improves overall system performance.

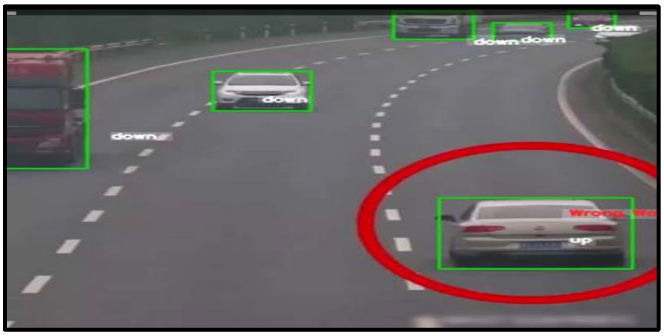

Fig -4: Direction Analysis of WSVDS

5.3 Frontend Dashboard Result

With an easy to use frontend dashboard, following Live Traffic Video Feeds and any detected vehicles (wrong side) is simple as well as being able to see real time notifications of Alerts, Cameras, Historical Information on any violation and evidence that has been documented. Using this dashboard as an interface, Traffic Authorities can access and analyze data

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very easily. Frontend Systems will enhance usability and make the overall Traffic Monitoring process more efficient and practical in an implementation environment.

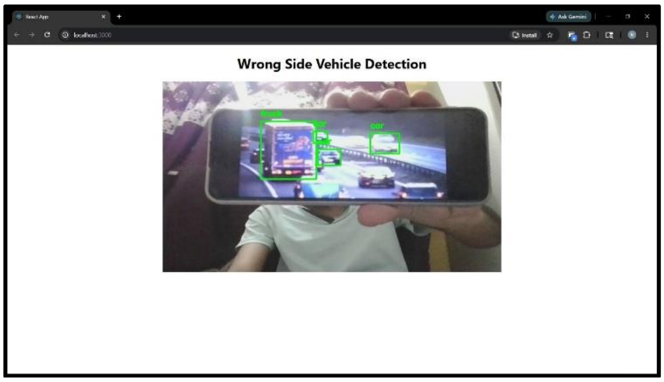

Fig -5: Frontend Dashboard Result

6. CONCLUSION AND FUTURE SCOPE

By using AI Technology to Identify both Compliance and Non-Compliance of Road Users in Real-Time, This system is designed to Enhance Safety on Roads and Automate the Monitoring of Your Traffic Management Process. The System Utilizes Security Cameras (CCTV) to Capture Images of Vehicles in Violation of Established Traffic Regulations while Combining Computer Vision & AI for Vehicle Detection; Basically, YOLO (You Only Look Once) Algorithm of Vehicle Detection and Tracking to Predict Movement of Vehicles Utilizing in Perspective the AI Intelligence of Centroid Tracking and the Deep SORT Algorithm. With The Wrong Side Vehicle Detection System for Example, We can Reduce the Level of Manual Monitoring Effort Required by Traffic Authority Staff to Identify Traffic Violations; Increasing The Accuracy of Violation Identification, While At The Same Time Improving The Overall Capability and Accuracy of All Authority Staff to Monitor the Status of Road Users and Monitor Traffic Flow Effectively.

Results showed that the system can successfully identify four distinct types of vehicles (car, bike, bus and truck) at any point in time and will accurately identify whether a vehicle is travelling in an intended or unintended direction based on trajectory and velocity information generated from the direction analysis module. Additionally, if a vehicle travels against the flow of traffic, the system will generate an immediate alert to users and the system will store evidence in a database to support enforcement actions, including images, timestamps, and address information. With an average detection rate of 95% and a low processing time, the proposed system demonstrates the potential to provide quality performance for real-time traffic monitoring systems.

This project will add greatly to future developments in smart city networks as well as intelligent transportation systems. Because this proposed model uses existing CCTV camera networks, it is scalable and cost-effective for both traffic management and road safety improvements. Additionally, the ability of the system to generate alerts and automate monitoring enhances the ability to enforce traffic laws while reducing human error and the amount of personnel needed for enforcement purposes. This should show how Artificial Intelligence (AI) and Deep Learning (DL) can successfully be used to address real-world issues in transportation and surveillance.

In coming years, the Project may integrate with smart traffic signals, mobile alert systems and cloud-based solutions to establish an entirely automated intelligent traffic management system. In addition, there is the potential to utilize superior AI based Predictive Analytics to determine the probability of an accident to prevent severe traffic violations from occurring by identifying and assisting with the correction of driver characteristics that will likely contribute to accidents. With ongoing enhancements and the advancement of technology, The Wrong Side Vehicle Detection System has a significant opportunity to be developed into industry-ready Smart Traffic Management Solutions that will significantly enhance roadway safety, decrease the number of traffic violations, and assist modern smart city transportation systems.

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