REAL TIME TRAFFIC RULES VIOLATION DETECTOR USING MACHINE LEARNING

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***Abstract*- The integration of real-time traffic rules violation detection and automatic number plate recognition using machine learning technologies heralds the emergence of a transformative paradigm in traffic management, ushering in the era of Virtual Traffic Police. By leveraging advanced ML algorithms, this system obviates the necessity of human traffic enforcement, offering an automated solution for monitoring traffic violations and identifying vehicles in real-time. The system's capabilities encompass the detection of various violations, including motorcyclists without helmets, and instances of triple riding, thus promoting safer road environments. Moreover, the ANPR component plays a pivotal role in simplifying traffic congestion by swiftly identifying vehicles and enabling seamless monitoring of traffic flow. The proposed model employs a camera-based approach to capture video footage, which is then subjected to ANPR techniques for plate localization and character recognition. The overarching objective of this project is to mitigate road violations and enhance traffic safety. Additionally, the system facilitates the generation of challans for detected violations, ensuring accountability and compliance with traffic regulations. Furthermore, by harnessing ANPR technology, advanced systems capable of identifying and tracing stolen or uncertified vehicles are introduced, bolstering efforts to combat vehicle-related crimes. This paper outlines the methodology, implementation, and potential impact of the proposed system in revolutionizing traffic enforcement and fostering a culture of compliance on the roads.**

Keywords: **CNN, YOLOV7, Machine Learning, Deep Learning, Tenser Flow, OpenCV.**

I. INTRODUCTION

The advent of real-time traffic rules violation detection systems powered by machine learning marks a pivotal moment in road safety management. By harnessing the capabilities of advanced algorithms, these systems analyze live video streams from traffic cameras, swiftly identifying instances of rule violations with unparalleled accuracy. Utilizing deep learning methodologies like convolutional neural networks (CNNs), these systems can detect a wide spectrum of violations in real-time, ranging from speeding and running red lights to illegal parking and improper lane usage. Unlike conventional methods reliant on manual oversight and prone to delays and errors, based on violation detectors operate autonomously, providing continuous monitoring and instantaneous alerts for non-compliance. Moreover, their adaptable nature allows customization to suit diverse road environments, including urban intersections, highways, and school zones. The data amassed by these systems holds immense value for traffic management authorities, aiding in pinpointing high-risk areas, analyzing traffic patterns, and implementing targeted interventions to enhance overall road safety. In essence, the integration of ML technology in real-time traffic violation detection represents a monumental leap forward in fostering safer, more efficient roadways, thereby mitigating accidents, saving lives, and mitigating economic costs associated with traffic-related incidents. This innovative approach not only streamlines the enforcement of traffic regulations but also offers a proactive solution to mitigate potential hazards on the road. By instantly flagging violations as they occur, authorities can swiftly respond to and address safety concerns, thereby reducing the likelihood of accidents and promoting smoother traffic flow. Additionally, the insights gleaned from the data analytics capabilities of these systems empower policymakers to make data-driven decisions aimed at optimizing traffic management strategies and infrastructure investments. As a result, cities and communities can create safer and more resilient transportation networks that cater to the evolving needs of their residents. Ultimately, the deployment of real-time traffic rules violation detection systems underscores a commitment to leveraging technology for the betterment of society, fostering a culture of road safety and sustainability for generations to come.

II. RELATED WORKS

The author in [1] present an Advanced systems for tracking and identifying stolen or unauthorized vehicles constitute a noteworthy development in the fields of security and law enforcement.These systems make use of automatic number plate recognition (ANPR) technology, which combines optical character recognition (OCR) with deep learning-based object identification methods in a seamless manner. Through the combination of these techniques, these systems are able to precisely locate license plates and extract correct characters from photos, which makes it easier to identify cars that are used in illegal operations. In order to guarantee all-encompassing coverage, the system also takes pictures from multiple perspectives, which improves its capacity to recognize cars in a variety of situations. However, under unfavorable circumstances like lengthy distances and bad weather, issues with the system's operation might occur. Notwithstanding these difficulties, the system's strong skills and potential to completely transform law enforcement procedures are highlighted by its dependence on deep learning and OCR technology. Sustained research and development endeavors are imperative in augmenting the resilience and dependability of these systems across various operational contexts, hence reinforcing their noteworthy function in law enforcement and security. These cutting-edge technologies are essential to preserving public safety and security, thus it is critical that they continue to be improved in order to satisfy changing requirements from law enforcement and guarantee community safety.

The author in [2] presents an exponential growth in vehicles necessitates efficient license plate recognition systems, and the paper under review offers a thorough summary of developments in this field with an emphasis on the fusion of image processing methods with contemporary technology like neural networks and deep learning. The suggested approach outlines a four-step process: input image preprocessing, license plate region extraction, license plate character segmentation, and character recognition. This approach acknowledges the complexity of license plate detection due to challenges like poor image resolution and diverse environmental conditions. With great care, the system demonstrates exceptional resilience, with high accuracy rates of 96.57%, 94.17%, and 97.5% in character recognition, segmentation, and license plate extraction, respectively.

The author in [4] presents The system under discussion is a sophisticated one that simplifies the process of locating and charging cars in parking lots by utilizing computer vision and character recognition algorithms. The method uses bounding boxes in conjunction with object identification algorithms to precisely locate cars in photos and then identify their license plates. This method significantly improves operational efficiency and saves time by reducing the need for manual interventions that are typically involved in license plate identification and charge computation. By speeding up and ensuring accuracy, automating the identification process reduces the possibility of human mistake that might arise during manual data entry. This reduces the possibility of errors resulting from human involvement and improves parking management's overall efficiency. However, some requirements must be met by the license plate photographs in order for the system to function properly. These requirements include sharpness, clarity, the lack of reflections, and a backdrop of light colors or white with no patterns. Following these guidelines improves the efficiency of character recognition algorithms, guaranteeing fast and dependable processing of license plate data. When everything is taken into account, the system offers a robust and dependable parking management solution that decreases errors and human labor while increasing accuracy and operational effectiveness.

The author in [5] presents a New image processing techniques are used by automated number plate recognition (ANPR) systems to detect automobiles, especially in heavily populated regions where traffic infractions are common. This system's use of an Optical Character Recognition (OCR) algorithm to precisely read license plates is a noteworthy feature that expands its functionality beyond that of conventional ANPR systems. Additionally, the system has monitoring features designed specifically for self-driving cars, which allows it to adjust to changing transportation technology. The system processes video data continually in order to partition road lanes and use object tracking algorithms to maintain lane information over time. This allows for accurate vehicle tracking. The technology preprocesses and analyzes vehicle photos to further improve accuracy by decreasing false positives by isolating zones of interest that particularly include number plates.

The author in [7] address the automated number plate recognition (ANPR) system, which is a key instrument for reducing traffic infractions and managing traffic congestion. The system endeavours to efficiently monitor and identify automobiles that are either stolen or unlawful by utilising sophisticated technology, including automatic number plate recognition. The main goals of the study are to examine the current approaches and to propose a new algorithm specifically designed for ANPR. The study offers an overview of state-of-the-art methods through a succinct analysis of several recognition algorithms. Furthermore, graphical representations of the suggested method are provided to clarify its operation. The testing and assessment findings included in the paper's conclusion highlight a notable accomplishment: a 90% accuracy rate in identifying vehicle number plates taken in a variety of settings, including various angles and climates.

III. METHODOLOGY

Fig.1 shows the architectural diagram outlines the typical process flow for developing a machine learning model. To clean and prepare the dataset, start with data pre-processing. Then, use feature engineering to extract pertinent features. After that, the data is divided into testing and training sets in order to assess the model. The testing data is used to evaluate the model after it has been trained using the training data. Lastly, the outcome is determined once the model's performance is evaluated.

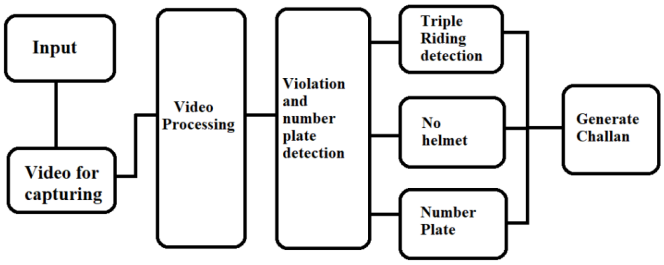

Fig. 1. Architectural Diagram

The data pre-processing phase is the first step in refining video data, with the goal of improving its quality and consistency for future analysis. Techniques like as scaling, normalization, and noise reduction are used to guarantee that the input data is clean and consistent, laying the groundwork for subsequent processing. Following that, the feature extraction phase becomes the focus point, with advanced algorithms such as CNN and Yolo used to extract significant features from pre-processed pictures. This step is critical in recognizing significant patterns and characteristics in the video frames, allowing the system to detect critical information indicative of various violations kinds. Finally, during the image classification phase, It also creates challans for infractions, which makes enforcement more effective. All things considered, this coordinated strategy improves traffic control by efficiently detecting infractions and applying laws instantly.

Stage 1 Data Collection and Preprocessing: The data collection and pre-processing is critical in gathering and preparing the dataset needed to train deep learning models. This module includes a number of operations aimed at compiling a complete dataset of violated videos from multiple sources, ensuring that no helmet , triple riding ,with helmet ,no number plate are all represented. The module begins by acquiring the dataset, which is then thoroughly cleaned to remove duplicates, outliers, and irrelevant photos, assuring data quality. Additionally, data augmentation techniques such as rotation, flipping, are used to improve dataset size and variety, hence improving model resilience. Finally, data normalization is used to standardize pixel values and colour channels across images, assuring consistency and compatibility with the next modules.

Stage 2 Image Classification: Using CNN for classification involves collecting discriminative characteristics from pre-processed violation images. CNNs are adept at learning hierarchical representations of picture information, allowing them to detect complicated patterns indicative of flaws such as no helmet and triple riding. During feature extraction, the CNN model runs input images through many convolutional and pooling layers like box bounding, NMS, eventually extracting abstract information useful for classification. These features capture the distinguishing properties of various defect types, allowing the model to differentiate between no helmet and triple riding ,helmet ,using learnt representations. During feature extraction, the CNN converts bytes values into a compact frames and informative feature space, allowing for precise categorization in the following phase.

Stage 3 Feature extraction: Beyond the techniques already covered, the feature extraction phase of the system given in the previous code contains many more significant ways to enhance its capabilities. The system primarily uses CNNs for object detection and categorization, enabling precise identification of various traffic violations in the video footage .CNNs are widely used for applications like license plate identification and vehicle detection because of their remarkable capacity to extract complex patterns and characteristics from picture data. Additionally, the system uses non-maximum suppression (NMS) to eliminate redundant detections and improve the identified object bounding boxes, guaranteeing the precision and effectiveness of the feature extraction procedure.

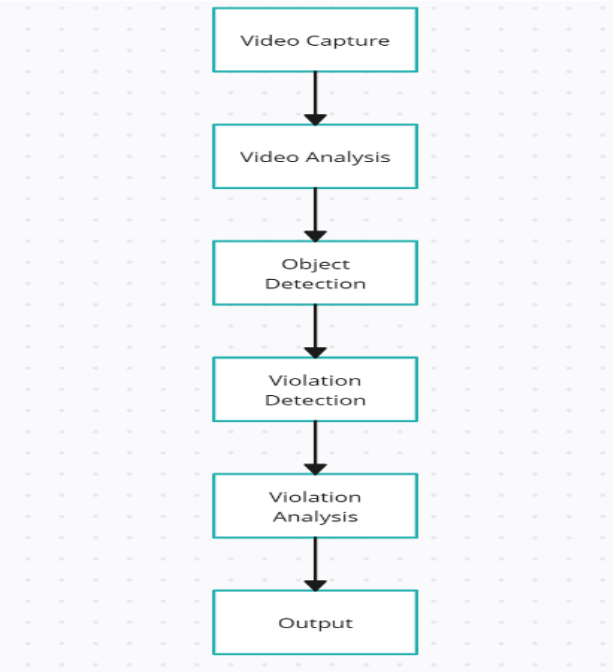

Fig. 2. Dataflow Diagram

The model uses dataflow in the real-time traffic violation detection system begins with the Video Capture stage, where a video of the traffic scene is captured using cameras installed at various locations such as traffic lights, police vehicles, or toll booths. This video feed is then passed on to the Object Detection stage, where an object detection system processes the video to identify and track vehicles such as cars, trucks, and motorcycles. Subsequently, the system proceeds to the Violation Detection stage, where it analyzes the detected objects to identify violations such as no helmet and triple riding. Upon detecting these violations, the system moves to the Violation Analysis stage, where it assesses the severity of the violations. Finally, in the Challan Generation stage, based on violation analysis, the system generates a challan containing detailed information about the detected violations, including the time, location, and fine amount, which is then issued to the offending vehicle owner or driver. This seamless flow of data through the various stages enables efficient and automated detection and penalty generation for traffic violations related to no helmet and triple riding. This multi-stage technique enables extensive flaw identification and analysis, improving the system's overall efficacy and dependability.

An information system's "flow" of data is represented graphically by a data flow diagram (DFD). Another tool for visualizing data processing (structured design) is a data flow diagram. It is customary for a designer to start with a context level DFD that illustrates how the system interacts with external elements. DFDs display the data flow into the system from external entities, the data flow between processes, and the logical storage of the data.

Algorithm:
Input: Traffic rules violated videos of vehicles.
Output: Classification of violated vehicles into no helmet ,triple riding and generating a challan for it.

Convolutional Neural Networks (CNNs) play a pivotal role in enabling automated analysis within real-time traffic rules violation detection systems. These systems leverage CNNs to extract vital information from video streams, which is essential for identifying and classifying various traffic violations such as no helmet and triple riding. CNNs excel in capturing intricate details within video footage, including edges, textures, and spatial patterns, which are crucial indicators of potential violations. The hierarchical architecture of CNNs enables the extraction of features at multiple levels of abstraction, allowing for comprehensive analysis of traffic scenes. This hierarchical approach ensures that the system can detect violations accurately across different scales, from minor infractions to more severe offenses. By leveraging CNNs, real-time traffic rules violation detection systems can achieve high levels of accuracy and efficiency, thereby enhancing road safety and traffic management efforts. Additionally, CNNs enable continuous learning and adaptation, ensuring that the system remains effective in dynamically changing traffic environments.

YOLO (You Only Look Once) is a state-of-the-art object detection system that revolutionizes real-time object detection tasks. Unlike traditional approaches that rely on region proposal techniques, YOLO frames object detection as a single regression problem, directly predicting bounding boxes and class probabilities from input images in a

single pass. This unique architecture enables YOLO to achieve remarkable speed and accuracy, making it highly suitable for applications requiring rapid and efficient detection of objects in images and video streams. YOLO's efficiency and effectiveness have made it a popular choice for various real-world applications, including surveillance, autonomous driving, and traffic management.

IV. RESULTS AND DISCUSSIONS

Dataset: Data collecting is an important stage in training any deep learning model, since it aims to collect a wide and representative set of data that reflects the problem domain. Using datasets from many sources providing traffic rules violations videos of vehicles, such as no helmet, triple riding, and riding with helmet videos, totaling over 400+ videos with various properties. These datasets were pre-processed and separated into training and validation sets, which were saved in the data/videos directory. It's worth noting that data collecting can be difficult and time-consuming, frequently necessitating data from many sources or manual labeling and annotation to assure quality and relevance. However, devoting time and effort to data collecting ensures the deep learning model's correctness and efficacy. Furthermore, the dataset was divided into 80% for training and Furthermore, the dataset has been divided into two parts: 80% for training and 20% for testing across all test instances.

Fig. 3. Dataset

To enable thorough training and assessment of the real-time traffic rules violation detection system, an extensive dataset was carefully selected. This dataset includes a wide range of photos and videos taken in actual traffic situations, guaranteeing the model's ability to reliably recognize different kinds of infractions. Every data point was meticulously chosen to encompass an extensive range of traffic infractions, such as speeding, running red lights, using the wrong lane, and parking illegally, among other things. The dataset includes photos and videos from various sources and scenarios, including differences in lighting, camera angles, and backdrop environments, to improve the model's generalization and performance. This varied representation reinforces the system's flexibility and dependability during deployment by reflecting the variability seen in real-world traffic enforcement circumstances. Moreover, data samples were collected from various traffic locations and conditions to capture a comprehensive range of violations, ensuring the model's robustness across diverse real-world contexts. Furthermore, to facilitate rigorous evaluation and benchmarking, the dataset was meticulously annotated with ground truth labels indicating the presence and type of traffic violation in each instance. These annotations served as invaluable guidance during model training and facilitated quantitative assessments of the system's accuracy and efficacy in categorizing traffic violations effectively.

Fig. 4. Results predicted by the model

Figure 4 represent the result of the classification of the input images is done based 3 major classes no helmet, triple riding, and riding with helmet.

The result signifies a substantial progression in the use of CNN and YOLO models, which is a key development in real-time traffic rule violation detection systems. These algorithms have demonstrated an impressive level of accuracy in identifying and classifying a broad variety of traffic offenses observed in images and videos. While the CNN model is more adept at categorizing infractions like riding without a helmet, riding in triples, and riding with a helmet, the YOLO model is more accurate in identifying and localizing objects and events related to traffic crimes. By incorporating these advanced models, the system enhances the detection process and makes it easier to promptly identify and accurately classify traffic violations. This development creates the framework for targeted efforts to improve road safety and traffic management as well as more effective enforcement of traffic laws. These findings also highlight the potential of ML technology to transform the transportation system and support the creating of safer, smarter cities.

V. CONCLUSION

Real-time traffic rule violation detection technologies, powered by advanced techniques such as computer vision and machine learning, mark a paradigm shift in traffic management and road safety. These systems leverage cutting-edge technologies like CNN with TensorFlow Lite and YOLO for precise and rapid detection of violations as they occur. By instantly identifying infractions such as no helmet and triple riding, they serve as a deterrent to reckless driving behaviors, ultimately reducing the risk of accidents on the road. Moreover, their real-time operation enables prompt intervention and enforcement actions, contributing to enhanced road user safety. Additionally, by automating the process of identifying and penalizing offenders, these systems optimize resource allocation and streamline law enforcement activities, leading to more efficient traffic operations. Furthermore, the data generated by these systems can be utilized to inform targeted traffic control strategies, thereby improving traffic flow and alleviating congestion on roadways. Ultimately, the deployment of real-time traffic violation detection systems holds tremendous promise for creating safer roads, enhancing traffic operations, and building smarter, safer cities for all.

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