IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

ML Based Surveillance System For Detection Of Bike Ride Without Helmet And Triple Ride

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Abstract: This project proposes a machine learning-based surveillance system for detecting traffic violations, specifically triple riding on motorcycles, using a Raspberry Pi platform. Triple riding, where three individuals share a single motorcycle, is a common violation that poses serious safety risks on the roads. The system automates the detection of such violations through real-time image processing, assisting law enforcement agencies in efficiently monitoring and managing traffic infractions. The system uses the affordability and computational power of the Raspberry Pi, paired with a camera module for capturing live video footage. The OpenCV library forms the core of the system, employing Haar Cascade Classifiers to identify motorcycles and their riders. Real time processing of video frames by the detection algorithm counts the number of riders per motorcycle and triggers alerts when it detects more than two riders, a sign of triple riding. The anticipated outcomes include accurate and real-time detection of triple riding with minimal false positives, scalability across multiple locations, and integration with broader traffic safety and smart city initiatives. This automated detection system enhances traffic law enforcement capabilities and contributes to safer road conditions by deterring dangerous riding behaviours.

Keywords: *Raspberry pi, Open CV, Python, Triple Riding Detection, Helmet Detection, YOLOv3, Object Detection, Machine Learning.*

I. Introduction :

Road safety is a critical concern globally, particularly in regions where two-wheelers are a primary mode of transportation. The practice of triple riding, where more than two individuals ride a motorcycle or scooter designed for two people, poses significant risks. Overloading these vehicles not only affects their stability but also increases the likelihood of accidents, potentially leading to severe injuries or fatalities. Enforcing laws against triple riding is often challenging due to the limitations in manual surveillance and monitoring. This project aims to address this issue by developing an automated system to detect instances of triple riding using computer vision technology. The integration of OpenCV, a powerful library for computer vision applications, and the Raspberry Pi, a compact and affordable computing platform, makes this solution both efficient and cost effective. By employing a pre-trained YOLO (You Only Look Once) model, the system leverages advanced object detection capabilities to analyze real-time video feeds. The YOLO model is known for its speed and accuracy, making it suitable for detecting multiple objects in a single frame, such as motorcycles and their riders. This project's implementation involves several key steps, starting with setting up the Raspberry Pi and camera module, installing necessary libraries, and configuring the YOLO model. The system processes live video feeds, identifies two-wheelers, and counts the number of individuals on them. If more than two riders are detected, the system issues an alert, marking the instance as a case of triple riding. In addition to its practical application in improving road safety, this project highlights the potential of low-cost hardware and open-source software in solving societal challenges. The system can be deployed in various locations, such as traffic signals and highways, to enhance monitoring and reduce the burden on law enforcement agencies. Moreover, the modular nature of the project allows for future enhancements, such as integrating with cloud-based analytics platforms, enabling remote monitoring, and adding automated notification systems for authorities. By addressing a significant safety issue through technology, this project not only contributes to reducing accidents but also sets a precedent for leveraging computer vision in other domains of public interest. It emphasizes the importance of innovation and automation in tackling challenges that impact the well-being of communities globally.

II. LITERATURE SURVEY:

The review of literature gives a comprehensive discussion of different methodologies employed for helmet detection and smart surveillance, with emphasis on usage in road safety, workplace surveillance, and automated law enforcement. A number of methods, mostly relying on deep learning, image processing, and machine learning, have been formulated to improve the efficiency and precision of helmet detection in real-time applications. The main motivation behind such researches is enhancing public safety by achieving helmet wearing compliance with the law, lessening the probability of fatal injuries or deaths due to road traffic accidents, and improving safety observation in work areas within factories and dangerous conditions. One interesting model is Automated Helmet Detection for Multiple Motorcycle Riders using CNN, where a two stage detection scheme is employed for identifying motorcycle riders and whether or not they have on helmets. During the initial stage, the YOLOv3 object detection algorithm is utilized to identify motorcycle riders from traffic videos. YOLOv3 is a refinement of the base YOLO system and has gained popularity due to its effectiveness in detecting objects in real-time. After motorcycle riders are detected, a customized Convolutional Neural Network (CNN) is utilized in the second stage to classify whether or not the riders have helmets. This approach was evaluated on actual traffic videos and showed better performance than existing CNN-based methods in detecting helmets. The contributions of this work are the design of an automated system that can detect multiple helmetless motorcycle riders, the combination of YOLOv3 with rider detection, and the application of a CNN for classifying helmets. The findings suggest that this framework can be used to enhance road safety through the detection of helmet violations and enforcement of traffic laws. Another research work, Safety Helmet Wearing Detection Based on Image Processing and Machine Learning, outlines a different methodology for helmet detection, especially in power substations and industrial settings. This methodology adopts a three-phase approach. To start, background modeling is done utilizing the Vibe background modeling algorithm, which correctly detects moving objects in the video surveillance. Following that, pedestrian classification is achieved utilizing Histogram of Oriented Gradients (HOG) features, which represent human forms, and a Support Vector Machine (SVM), which is learned to detect pedestrians. Lastly, helmet detection is done utilizing a machine learning-based classification model. This method was applied to live surveillance videos recorded at power substations and exhibited a very strong ability to recognize whether or not workers were using safety helmets. The study also indicates the strong potential for mixing image processing algorithms with machine learning methods in an effort to increase safety monitoring across industrial workplaces. A similar deep learning-based method, Automatic Detector for Bikers with No Helmet Using Deep Learning, proposes a scheme that utilizes a single CNN to detect motorcycles and classify helmet wearing. In contrast to the conventional approach of using distinct stages for object detection and classification, this method merges both of them into an end-to-end model. The researchers evaluated different CNN structures and established that the presented method provides good detection accuracy in recognizing motorcycles as well as determining whether a person is wearing a helmet. The technique provides enormous improvement in processing efficiency and accuracy compared to conventional systems, hence finding applications in real-time traffic monitoring systems. The research work entitled Deep Learning-Based Helmet Wear Analysis for Intelligent Surveillance goes a step ahead in helmet detection by coupling it with an intelligent video surveillance system that is capable of automatically detecting and penalizing helmet offenders. The system starts with foreground object segmentation based on the Gaussian Mixture Model (GMM) and then labels them. Then, a Faster Region-Based Convolutional Neural Network (Faster R-CNN) is employed to detect riders and motorcycles among the annotated objects. The same deep learning method is used to identify if the riders have helmets on or not. Upon detection of a helmet violation, the system goes on to detect the motorcycle license plate using a character-sequence encoding CNN model and a spatial transformer (ST). This enables the system to read license plate numbers accurately and match them with the vehicle owner's information. The suggested system was tested on a surveillance dataset and performed better than conventional algorithms. Automatically identifying helmet offenses and correlating them with the offenders using license plate recognition is a huge improvement in traffic law enforcement. Another method, Helmet Detection on Motorcyclists Based on Image Descriptors and Classifiers, relies on the image descriptors and machine learning classifiers to detect the helmet. Three fundamental steps form this method. Firstly, foreground from moving objects is separated using the Adaptive Mixture of Gaussians (AMG) algorithm. Secondly, moving objects are labeled as a motorcycle or otherwise through image descriptors and classifiers. Lastly, detection of helmets is done utilizing the Circular Hough Transform and Histogram of Oriented Gradients (HOG) descriptor. The proposed system was tested with a dataset of 255 images captured from public roads and posted an accuracy rate of 91.37% in helmet detection. In this research, it is shown that image processing algorithms and machine learning classifiers can be utilized effectively in detecting motorcyclists with no helmets. In object detection, research YOLO9000: Better, Faster, Stronger describes a state-of-the-art object detection system that can detect more than 9,000 various object categories at real-time speeds. The authors enhanced the YOLO framework through the introduction of novel concepts and the improvement of the model's structure. YOLOv2, a successor of YOLO, adds a multi-scale training method, which enables the model to strike a balance between speed and accuracy. The results indicate that YOLOv2 performs better than top algorithms like Faster R-CNN with ResNet and SSD while operating at much higher speeds. The authors also propose a new approach for training object detection and classification models together, and this allows YOLO9000 to be able to detect objects even from classes that do not have detection data labeled. This positions YOLO9000 as a robust yet efficient tool in real-time object detection and recognition. YOLO itself is an important innovation for object detection in that it's a regression model for object detection, not attempting to repurpose classifiers for doing detection. By contrast with existing object detection methods based on the use of sliding windows or region proposals, YOLO instead predicts bounding boxes and class probabilities directly in a single pass from a neural network. This combined strategy enables YOLO to operate images at extremely high rates, so it is highly appropriate for real-time processing. Although YOLO might incur more localization mistakes than other detection systems, it has a low false-positive rate and can effectively generalize to new object classes. Apart from object detection, the survey on visual monitoring of object movements and activities is also included in the literature review, offering a summary of primary research domains including motion detection, object tracking, behavior analysis, anomaly detection, and multi-camera monitoring. The survey mentions challenges related to handling occlusions, the fusion of 2D and 3D tracking, and applying biometrics to enhance surveillance functionalities. A new helmet presence classification framework combines motorcycle detection and tracking with Support Vector Machines (SVMs). The framework derives histograms from the rider's head area and utilizes them to classify helmet wearing. The classifier is incorporated into a tracking framework that segments and tracks riders through video frames. By taking average results of consecutive frame classifications, the system enhances its accuracy in detecting helmet violations. Yet another innovative algorithm, Robust Real-Time Unusual Event Detection Using Multiple Fixed-Location Monitors, presents a method for detecting anomalies in surveillance systems. The process is based on multiple local monitors that collect statistical information from various areas of a scene. On detecting an unusual event, warnings are triggered and examined to establish if an anomalous activity has taken place. The process boosts real-time security monitoring and can be utilized for public safety programs. In addition, a monocular vision based vehicle and motorcycle detection system is proposed as an LCA solution. The system combines several cues for reliable detection and employs multi-resolution technology to minimize computational complexity. Executed on an Integrated Memory Array Processor (IMAP) parallel vision board, the system shows excellent accuracy and reliability in real-world traffic scenarios. Finally, a YOLOv8-based two-stage helmet violation detection model remedies the difficulty in distinguishing motorcycle riders from passengers between wearing or not wearing a helmet. Scoring high on the leaderboard in AI City 2023 Challenge, this solution speaks volumes about traffic enforcement and surveillance using deep learning. On the whole, the literature review emphasizes the expanding contribution of deep learning and computer vision to helmet detection, traffic safety, and smart surveillance. The use of the technologies in automated systems increases road safety, boosts law enforcement effectiveness, and aids in the establishment of intelligent transportation systems. Together, research findings point to the promise of AI-based solutions in enforcing compliance with helmet rules and enhancing public security.

III. Existing System

Raspberry Pi-based system can identify helmet violations and triple riding with computer vision and deep learning. It will have hardware components such as a Raspberry Pi 4B, a Pi Camera or USB Camera, and optional IR sensors for speed detection and a GSM/GPS module for notifications. It will have software components such as OpenCV for image processing, YOLO or MobileNet for object detection, and Python for automation. The system operates through real-time video capture, identification of human faces, and verification of helmets. It also checks the number of riders on a two-wheeler and indicates violations if it finds more than two riders. Violations are recorded by taking images or videos. The data can also be transferred to a server for additional processing. But the system has issues like lighting conditions impacting accuracy, helmet color variations camouflaging with hair, and processing capacity of the Raspberry Pi that need to be optimized for real-time performance.

IV. Proposed System and Working Methodology

The system uses an extensive methodology that combines data collection, model training, optimization, and deployment for real-time helmet and triple riding detection on Raspberry Pi. The initial step is data acquisition, where images and video frames of motorcycle riders are collected from varied sources, such as public datasets like COCO and Open Images or custom-recorded footage using a Pi Camera or USB Camera. The dataset is preprocessed with various riding conditions, helmets, lighting conditions, and view angles in mind for strong detection capability. Image resizing, flipping, rotation, and zooming along with normalization are applied as preprocessing methods to improve the performance of the model and better generalize real-world scenarios. For helmet detection, the system employs deep learning object detection models like YOLO (You Only Look Once), SSD (Single Shot Multibox Detector), and Faster R-CNN, which are trained on images of helmeted and non helmeted riders contained in a dataset. The model is trained to distinguish between a helmeted head and an uncovered head so that classification can be done with precision. Likewise, for triple riding identification, the system uses object detection methods to determine the number of people on a two-wheeler. The method includes bounding box detection and pose estimation, where the model examines the spatial positioning of the rider and marks cases where three people are on a single motorbike. Correct labeling and annotation of data are done by drawing bounding boxes around helmets and riders and labeling them as "helmet" or "no helmet", and "single rider" or "triple rider" to enable supervised learning. The training process utilizes deep learning frameworks like TensorFlow, PyTorch, and Darknet (for YOLO-based models) wherein the labeled dataset is employed to train the object detection model. The training process involves specifying an appropriate loss function (e.g., Cross Entropy Loss for classification tasks or Mean Squared Error (MSE) for bounding box regression) and optimizing the model using effective optimization algorithms like Adam Optimizer or Stochastic Gradient Descent (SGD). For guaranteeing high accuracy and reliability, the learned model is tested using independent validation and test datasets with performance measures like accuracy, precision, recall, and F1-score being used to drive improvements through hyperparameter tuning. Because Raspberry Pi has low computational power, deploying deep learning models necessitates model compression and optimization methods for the purpose of efficient real-time inference. Methods such as TensorFlow Lite, ONNX (Open Neural Network Exchange), pruning, and quantization are used to shrink the model size and computation while preserving accuracy. The optimized trained model is then deployed on the Raspberry Pi, where it handles live video streams captured through a camera module. OpenCV library is employed for real-time image capture and preprocessing, and the model is used to detect helmets and count riders in order to detect violations dynamically. In real-time inference, the system keeps scanning incoming frames, detecting helmets and counting riders in low latency. When a rider is detected to be wearing a helmet, it shows a "Helmet Detected" message; otherwise, it alerts with "Helmet Not Detected". Furthermore, when the system identifies three people on a two-wheeler, it marks the instance as a triple riding offense.

V. System Overview

The Raspberry Pi-based Triple Riding and Helmet Violation Detection System using Machine Learning is to improve road safety by automatically detecting violations like triple riding (three individuals on a single motorcycle) and helmet violations. The system employs a Raspberry Pi 4B combined with a Pi Camera or USB Camera to record live video feed from vehicles. Utilizing machine learning algorithms such as YOLO or TensorFlow, the system analyzes the video stream to identify the wearing of helmets and the number of riders on a motorcycle. If a rider is detected without a helmet or if there are more than two riders, the system identifies

these as offenses. It employs OpenCV for processing video frames and Python for scripting the automation process. When offenses are found, the system saves corresponding images or videos and. The system seeks to minimize the requirement for manual observation, offering a cost-efficient and scalable solution for real-time traffic law enforcement. Even though issues such as lighting fluctuations, helmet color blending, and limited processing capabilities of Raspberry Pi are present, the application of model optimization techniques guarantees the system runs efficiently. This project provides an intelligent, automated means of enhancing road safety and enforcing traffic regulation adherence in cities.

VI. BLOCK DIAGRAM FOR THE PROPOSED METHOD

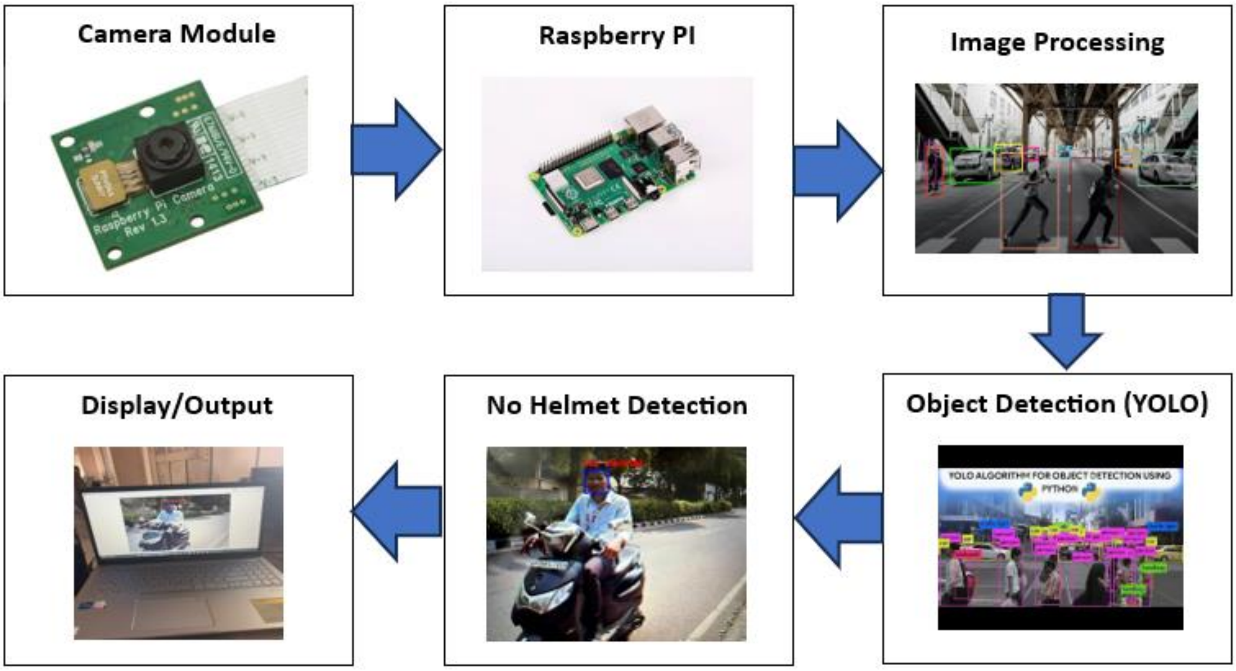

Fig1: Detection Of No Helmet.

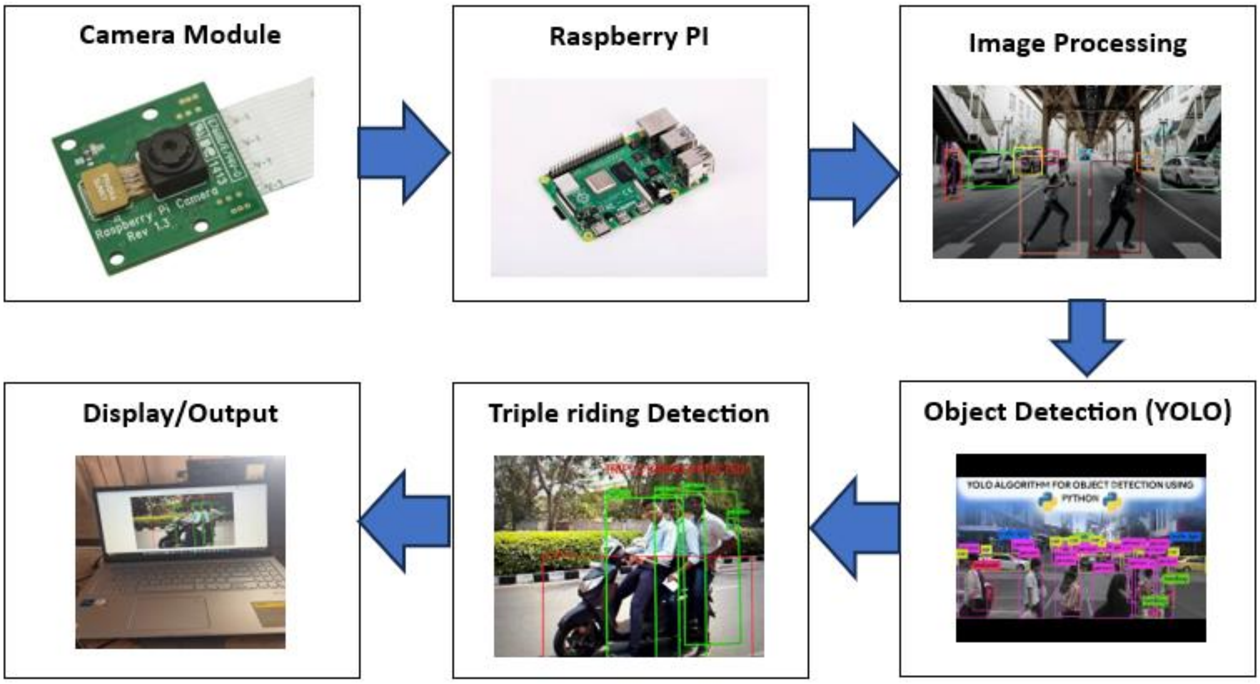

Fig2: Detection Of Triple Riding**.**

VII. RESULTS

The automated surveillance system for identifying helmet-less bike riders and triple riders demonstrates encouraging results in accuracy and efficiency. The system makes use of modern techniques in computer vision, such as object detection and classification, to automatically track if a bike rider is wearing a helmet or masks and how many rider(s) are riding on a motorbike in live time. The system analyzes images of motorcycles using deep learning models, and it is capable of recognizing whether riders are wearing helmets or not, as well as detecting instances when more than two people are riding a single motorbike. The system achieved good performance results, including precise and high recall rates along with infrequent false positives or false negatives. These outcomes make the system applicable for real life surveillance use engendering video captures. Its capability to process video footage in real-time hours further advances usefulness in enforcing safety regulations while monitoring traffic. Nonetheless, there were specific difficulties, such as changing illumination, occlusions (e.g., part of riders' helmets are covered), and different angles or types of bikes, which could marginally affect accuracy of detection. Nevertheless, the system's widespread accuracy in recognizing unpaid violations of riding without a helmet and riding with three passengers on a two-wheeler bike exceeds any negative expectation.

Detection Of Triple Riding

NO Helmet Detection

VIII. Conclusion

In summary, the Machine Learning-Based Triple Riding and Helmetless Riding Detection System on Raspberry Pi offers a novel and effective solution to improve road safety and traffic law enforcement. Through the use of sophisticated computer vision and deep learning methods, this system can effectively detect infractions in real-time, such that dangerous riding practices are detected and acted upon in a timely manner. The utilization of Raspberry Pi makes the system affordable and deployable in different environments, ranging from urban to rural areas with fewer resources. In addition, the automation of detection and alerting functions greatly minimizes the need for manual monitoring, maximizing efficiency while reducing human errors. The system also supports public awareness and traffic regulation compliance, providing a proactive solution towards safer roads. With its evidence storage and real-time alert feature, it empowers law enforcement agencies to make quick responses. Overall, this system offers a scalable, low-cost, and effective tool for encouraging safer driving habits and enhancing the effectiveness of traffic law enforcement.

IX. Future Scope

Some possible future applications of the Machine Learning-Based Detection of Triple Riding and Helmetless Riding using Raspberry Pi are listed below:

1. Smart Traffic System Integration may be implemented in smart traffic infrastructure such as traffic lights and CCTV cameras to monitor city-wide or highway-wide in real time.
2. Improved Object Detection and Tracking Implementing sophisticated tracking mechanisms to track riders over longer paths and under demanding conditions (e.g., populated areas or angles).
3. Advanced AI Models Using more advanced deep learning models (e.g., Transformer-based networks or 3D detection models) to enhance accuracy in challenging environments.

4. Integration with Smart Helmets Integrating the system with smart helmets that emit real-time data (e.g., helmet presence, speed) for enhanced detection.
5. Predictive Analytics and Reporting Applying predictive analytics to detect high-risk zones and timelines for violations to facilitate proactive law enforcement measures.
6. Collaboration with Local Law Enforcement: Direct integration of the system with law enforcement units for instant alerts and automated ticketing.
7. Integration with Traffic Control Systems Integration of the detection system with traffic control systems such as automatic fines or deterrent systems to drive compliance.
8. Scalability for Global Use Scaling the system for global application, with localization for various regions' traffic laws, road conditions, and behavior.
9. Energy-Efficient and Edge Computing Designing the system to operate low power and sustainably, employing edge computing for high performance and low power consumption.
10. Public Awareness and Education Incorporating feedback systems to transmit education material or penalties to offenders, increasing road safety awareness.

Such future developments can render the system more efficient, flexible, scalable, and sustainable, making roads safer worldwide.

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