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Helmet and Number Plate Detection

D. Tharun Reddy[1]; N. Durga Prasad[2]; M. Sheshu Kumar[3] and Dr. A. N. Satyanarayana[4] (Professor)
1 to 3 Students of B. Tech, ECE Department, Sreenidhi Institute of Science and Technology, Hyderabad
Electronics and Communication, SNIST, Hyderabad

Abstract:- An important use of computer technology in recent years has been the automatic helmet recognition of motorcy clists in real-time surveillance film. Deep learning methods are becoming more and more popular as a result, especially for object detection and classification. Nevertheless, a number of issues, including limited resolution, inadequate lighting, adverse weather, and occlusion, restrict the accuracy of current models in identifying motorcycle helmets. A unique method that makes use of the Faster R-CNN model has been put out to address these issues. Using the input image as the starting point, this method first trains the Region Proposal Network (RPN), and then it uses the RPN weights to train the Faster RCNN model. The goal of this method is to increase helmet detection accuracy in live surveillance footage. This method's experimental results have demonstrated encouraging results, with a 95% accuracy rate in identifying motorcycle helmets in live surveillance footage. This illustrates the promise of deep learning approaches in the field of automatic helmet detection for motorcyclists in real-time surveillance film, as well as the efficacy of the suggested strategy in overcoming the issues encountered by current models.

Keywords:- *Helmet, Faster-RCNN, CNN, Deep Learning, Region Proposal Network, Surveillance Videos.*

I. INTRODUCTION

The general cause of the rise in motorcycle accidents in recent years has been the riders' haste, negligence, and recklessness. Since head injuries account for the majority of fatalities in these incidents, preventative measures are imperative [1]. A tested safety precaution that dramatically lowers the chance of brain damage in the event of an accident is wearing a helmet. However, the majority of brain injuries among motorcycle riders are caused by their failure to abide by traffic laws mandating the usage of helmets.

In countries like India, where motorcycle usage is high, the problem of non-compliance with helmet laws is particularly acute. To address this problem, a cost-effective solution using computer vision-based automated systems for helmet detection can be employed [2]. This solution can be easily integrated with existing video surveillance systems and has the potential to significantly reduce the workload of traffic police.

The key objective of this work is to prevent significant injuries caused by motorcycle accidents by applying computer vision-based automatic motorcycle helmet recognition. The proposed solution will identify riders who are not wearing helmets in real-time and alert authorities to take appropriate action. This technology can play a vital role in promoting compliance with helmet laws and improving overall road safety.

In summary, the increasing number of motorcycle accidents and head injuries among riders highlight the importance of implementing measures to promote helmet usage. The pro- posed solution using computer vision-based automated helmet detection technology can effectively address this issue, par- ticularly in emerging nations with high motorcycle usage [5]. The primary goal is to prevent significant injuries caused by traffic accidents by promoting compliance with helmet laws through automatic helmet detection systems.

- *Problem Definition*

The main objective of this research is to build an automatic helmet violation detection system with the help of deep learn- ing approaches of computer vision. The system is designed to analyze surveillance videos captured by cameras installed on roads or in public places and identify whether motorcyclists are wearing helmets properly or violating helmet laws.

II. RELATED WORKS

Different approaches have been put forth by numerous researchers to address the issue of autonomous helmet iden- tification in real-time traffic situations. The section below discusses these techniques.

In the beginning, researchers employed computer vision techniques like HOG, SURF, and SIFT for machine learning to automatically detect whether motorcycle riders were wearing helmets or not.

Many analyses of the traffic on roads, with the identification, categorization, and tally of cars as well as the detection of helmets, have been carried out in recent years. The first step in any research on vehicular traffic development should be to identify and classify the vehicles that are driven on public roadways. As such, some related studies are analysed here.

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A framework for the detection of road safety violators who ride bicycles without wearing helmets was proposed by KunalDahiya [1]. The suggested framework helps the traffic police find these offenders in unusual settings, such the blazing sun, etc. The experimental results shows the accuracy of 93.80% for violator detection. With an average processing time of 11.58 milliseconds, this data is appropriate for real-time applications. Additionally, the suggested structure automatically adjusts, with minimal tweaking, to new cases as needed. It is possible to expand this framework to identify and report violators' license plates.

Chiu C-C [2] suggested a computational vision system that aims to monitor and identify motorcycle riders that are partially hidden by another vehicle. The approach assumesthat the area around the helmet is round in shape. The limitations 3 of the picture are computed over the area around the motorcycle, or the helmet's potential zone, in order to identify the helmet. Then, recursively count the number of edge points which form a circle. In case this number exceeds or equals a current value, the region will be associated with a helmet throughout the system calibration process. The system concludes that there is probably a motorcycle nearby when it finds a helmet. During the calibration phase of the system, the operator needs to input certain measures like the height, angle of the camera, and helmet radius. In the event that any conditions change, like the height of the camera or the road where the device is being used.

Leelasantitham and Wongseree [3]devised a method that uses traffic engineering techniques to detect moving autos. Five pairs of cars were present. The first category consisted of tricycles, motorbikes, and bicycles. Vans and sedans were among the cars in the second category. Small cars and minibuses fall under the third category. The fourth group consisted of medium and large buses. The fifth category consisted of trailers and large trucks. The features that were used for classification were the length and width of images. The database consists of just 76 images, casting doubt on the results' dependability. Remember that the system depends heavily on the road where the photos are taken. Consequently, if the same system is used on a different route, all mea- sures—like the image's length and width—should be adjusted. A technique utilizing image processing to offer data on the number of traffic offenders in a given area was proposed by Tahniyath Wajeeh [4]. It snaps a picture as proof and builds an exhaustive list of all cyclists that don't wear helmets when driving. Because OpenCV, Tensor Flow, and other open-source, free technologies are used, the software is significantly cheaper. This technique was tested to provide complete proof and accurate outcomes under optimal lighting circumstances.

The more people that are aware of the system, the greater its impact. Messelodi S. presented a method for vehicle classification and segmentation [5]. To categorize the artifacts, eight 3-D models were developed in order to classify them. The sizes of the vehicles, which differ according to the kind of vehicle, were used to calculate these models. A variety of versions were built, including ones for motorbikes, bicycles, small and large cars, minibuses, trucks, buses, and pedestrians. For every vehicle that is caught, a model is built to be assessed to the models made for every kind of vehicle. The vehicle class is determined by identifying the model that most closely reflects the type of the seized vehicle. A constraint of this research is that only one design was employed for both motorcycles and bicycles. Furthermore, it has been shown that these kinds of objects cannot be well described by categorizing the vehicles based only on geometrical data. Another problem with this strategy is that some parameters, such as focal distance, angle, and camera height, should always have the same values. A vehicle would not match the models if these features were changed, hence new ones ought to be created. According to this research, the system was not able to be implemented on certain public roadways due to the absence of a location forthe camera.

An Approach for MVD Helmet Detection by Rohith C. A suggested using Deep Learning. [6]. The chosen condition for categorizing the recorded frames is a person operating a two- wheeler while donning a helmet or not. First, they categorize photos that show people riding two-wheelers or not. Next, examine the photographs that have been classed to get the data set according to the condition. Any captured frames that don't meet the aforementioned requirements for photographs will be ignored or deleted. The Caffe model is the one that is utilized for extraction and detection. The accuracy score of the suggested model is 86%. The Inception V3 model serves as the categorization model. The suggested model had a 74% validation accuracy score.

Prity Kumari [7] proposed a system which is is extremely effective for the protection purpose of the user. User needs to wear helmet to ride a motorcycle and therefore traffic rules are monitored by the rider. This method is below pocket management that's riding the two wheeler vehicle having safety in hand and in affordable. This approach uses basic functionalities. It offers the cyclist increased security. Sinceall of the tools and libraries used in the project are freely available, they are all very adaptable and reasonably priced.

Addressing the problem of inefficient traffic organization was the main objective of the project's engineering. From now on, the end will state that if coordinated by any traffic managementdepartments, it would make their work more efficient and easy. It is demonstrated by Romuere Silva [8] that the LBP de- scriptor outperformed the HOG and Haar Wavelet descriptors in terms of robustness for the task. By pattern joint distri- bution, the LBP descriptor characterizes the regional texture pattern. Motorcycle texture patterns bolster the efficiency of the LBP feature-based classifier. The SVM classifier produced accurate findings. The performance of the SVM during thetraining phase is its primary benefit. SVM often trains more quickly than Radial Basis Function Networks (RBFN) and Multi-layer Perceptrons

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(MLP). The Random Forest algorithmproduced the accurate result in the helmet detection step. The collective approach of CHT, HOG, and LBP producesan excellent, satisfactory outcome with regard to the hel-met detection. This makes sense since the feature vector isconstructed by combining edge (HOG), texture (LBP), and geometry (CHT) insights.

A strategy for keeping an eye on motorcyclists who choose not to wear helmets is suggested by the GayathriV [9] re- search. A PC visual system including elements for moving item section, moving item configuration, and helmet recogni- tion would be useful to the traffic specialists. The proposed framework will also assist the traffic police in finding these of- fenders in challenging circumstances, such intense heat, etc. In order to overcome obstacles, propelled following computations are usually necessary.Night vision cameras are commonly employed to use the location framework when there is no light. Further examples of both positive and bad behavior will be stored in response to requests to enhance the conjectural capability of the framework in the future. Work with the front- end video catch modules as well.

According to Narong Boonsirisumpun's research [10], an experiment was carried out to detect and sort motorcyclists into groups according to whether or not they wear helmets. Four convolutional neural networks (CNNs) are employed in these tests: VGG16, VGG19, Google Net or Inception V3, and Mobile Nets. To complete the image recognition phase, these models are combined using the SSD approach.

How to spot motorcycle riders who aren't wearing helmets is covered by Romuere Silva [11]. They propose dividing a CV system into three components: detection, classification, and segmentation of moving objects. The results are what was anticipated. The MLP classifier using the HOG descriptor pro- duced the most favorable outcomes, with a 0.9137 accuracy.

The tracking algorithm used was the Lucas-Kanade tracker algorithm [12]. The tracking of objects predicts when a car andan individual will crash. The technology will sound a warning if a car and a pedestrian cross the crossing at the same time. Given that a pedestrian may alter their course after the system provides a warning, there is a high risk of false positives with this technology.

According to Dr. A. Radhika [13], The convolutional neural network-based method detects helmet wear by using riders of motorcycles and two-wheelers. To determine if bike riders are wearing safety helmets, the model uses SSD Mobile Net and the YOLO algorithm. Three portions are built from acollection of photos with various helmets in order to train and test the model. TensorFlow is a framework used for training the model. A helmet detection model is produced once the detection model's mean average precision (mAP) is stableduring training and testing.

Adaptive background subtraction is used in C. Vishnu's [14] proposed framework for the automatic detection of motorcy- clists who do not wear helmets. This technique is resistant to anumber of problems, such as poor lighting and video quality. A more dependable system is produced by using machine learn- ing for autonomous learning of discriminating models for taskclassification, which raises the rate of identification and lowers the amount of erroneous alerts. Using two genuine video records, the trials effectively identified 92.87% of offenders with a small erroneous alert rate of 0.50%, demonstrating the effectiveness of the suggested technique.

Jimit Mistry [15] offers an automated helmet detection technique based on CNN. They use two stage YOLOv2 models to increase the helmet detection precision. First, human detection is guaranteed by the guaranteed by the YOLOv2 model, which used the COCO data collection for training. Asa result, fewer helmets will go unnoticed. The edited photos of the observed person provide input to the next YOLOv2 model, which was trained using our data set of photos with helmets. The proposed methodology has been tested using a range of helmeted image settings. Additionally, they assessed the numerical measures on the test photos and contrasted them with other cutting-edge techniques. Our approach has a high accuracy in helmet detection, and its dependability and resilience are demonstrated by experimental results and quantitative measurements on a range of circumstances.

III. PROPOSED WORK

The first step in helmet recognition is detecting a moving vehicle. It is the first stage before performing more advanced activities like vehicle tracking or categorization. Rather than processing the full video at once, the example begins with collecting an initial video frame in which the moving objects are separated from the background.

Processing merely the first few frames allow you to takethe necessary steps to process the video. To establish 6 the Gaussian mixture model, the foreground detector requires a fixed number of video frames The foreground segmentation procedure is rarely perfect and frequently contains unwanted noise. Following that, we locate the bounding boxes of each connected component that corresponds to a moving vehicle.

The next step is to categorize the moving vehicle extracted in the previous section. A vehicle can be divided into two types: two wheelers and four wheelers. Because we wish to identify the helmet, we are only intrigued in two wheelers. Only if a two-wheeler is identified does the system proceed. Otherwise, it discards this vehicle and searches for new ones, and the cycle continues.

We obtained the training data required for vehicle clas- sification on our own. We photographed numerous autos in various positions. we were collected for both the two- wheeler and four-wheeler groups. When there are an equal number of training photos from both classes, the

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problem of classimbalance is eliminated, and the classifier performs better.

The training images feature a car encircled by intriguing features including buildings, walkways, trees, and other loud objects. The images show a car as it would often be seen on the road. It is convenient to employ synthetic images since they enable the creation of a large variety of training samples through image augmentation. A separate set of images is used to evaluate the classifier. This dataset is adequate to train and evaluate the efficiency of different deep learning techniques in order to assess the model's viability, even though it is not the most exemplary of moving objects in the real world. The images underwent a grayscale conversion. Raw pixel values were input into the classifier.

To figure out if the person driving is using a helmet, we utilize the same technique used to determine the kind of vehicle. A helmet detector is trained using edited photos of two-wheeler photos with the rider's helmet region in the center. We were nevertheless managed to keep the class balance by employing this strategy, as evidenced by the equal number of photos including cyclists wearing helmets and those without. To find the best machine learning classifier for this assignment, we experimented with a number of them.

IV. METHODOLOGY

The Automatic Helmet Violation Detection system proposed in this research involves several key steps, beginning with the collection of diverse video surveillance data capturing various traffic scenarios with motorcycles. The dataset undergoes annotation, where regions of interest (ROIs) are labeled to identify instances of helmeted and non-helmeted motorcy- clists. Pre-processing steps include frame extraction and data augmentation to create a robust and representative dataset for training and testing.

Because of its efficacy in object detection tasks, the Faster R-CNN structure is selected as the main model for helmet recognition. To take use of universal object detection features, transfer learning is used by initializing the model with pre- trained weights on a sizable dataset such as COCO. Using the annotated dataset, the Region Proposal Network (RPN) is trained, and the Faster R-CNN model is refined. Stochastic gradient descent (SGD) is one of the optimization strategies used to minimize the loss function and improve the accuracy of the model.

A approval set is used as part of the model evaluation process to track performance during training and avoid over-fitting. Performance metrics like precision, recall, accuracy, and F1-score are used to assess how well the model detects helmets. As part of the experimental results, real-time film is used to assess the trained model's accuracy in recognizing helmet violations through live surveillance testing. To assess the model's performance under demanding scenarios such as poor resolution, unfavorable weather, and occlusion, robust- ness testing is carried out.

In summary, the Faster R-CNN model, a deep learning approach used in the proposed methodology, is used to managethe critical issue of the helmet violation detection in real-time surveillance films. The system's goal is to increase the helmet compliance among motorcyclists in order to promote roadsafety. The evaluation phase will shed light on the system's efficacy and possible effects in practical situations.

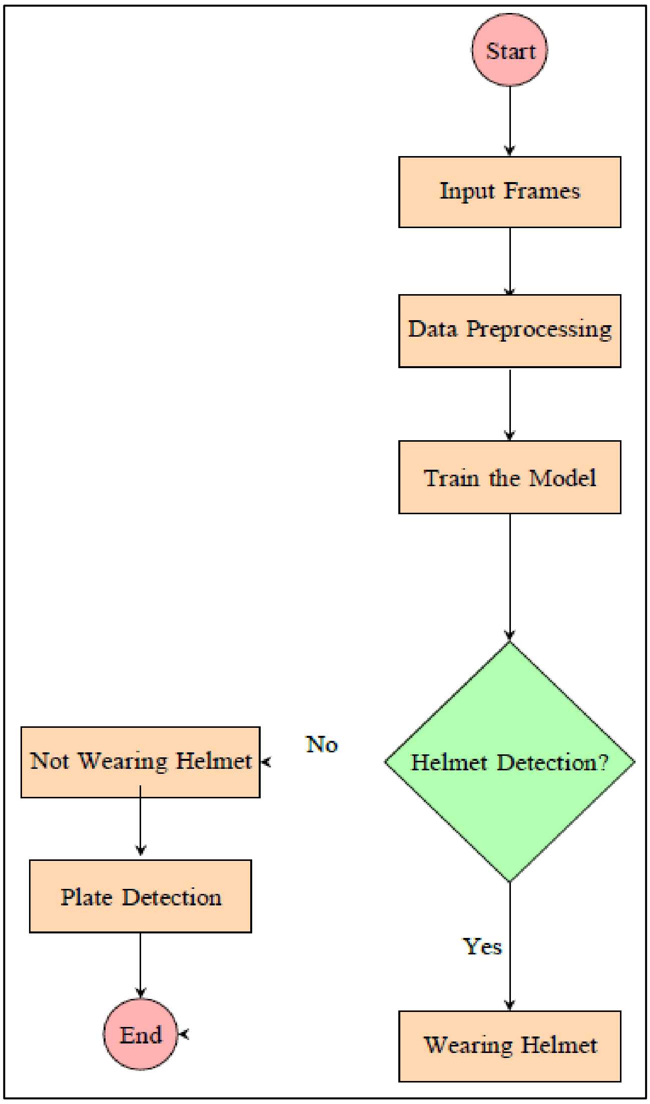

Fig 1 Flow Chart

➢ *COCO*

The COCO (Common Objects in Context) dataset serves as a valuable resource for training the Automatic Helmet Violation Detection system. This dataset, widely used in computer vision research, contains a diverse array of images with detailed annotations, making it suitable for pre-training deep learning models. By leveraging COCO, the Faster R- CNN model is initialized with pre-trained weights, enabling the system to learn generalized features for object detection. The richness of object categories and contextual information in COCO enhances the the model's capacity to identify and cate- gorize various items, contributing to the system's effectiveness in identifying motorcycle helmets in real-time surveillancevideos.

- *Faster-RCNN*

Faster R-CNN (Region-based Convolutional Neural Net- work) represents a groundbreaking advancement in the realm of object detection within computer vision. One of its key in- novations lies in the integration of a Region Proposal Network (RPN), which significantly enhances efficiency by proposing candidate regions likely to contain objects. This streamlining of the detection process mitigates the speed limitations that plagued earlier models, thereby enabling Faster R-CNN to operate swiftly and accurately even in complex visual en- vironments. The model's operation unfolds in two distinct stages: firstly, the RPN generates these candidate regions, followed by a subsequent stage that handles classification and refinement of these proposals. Through this two-stage ap- proach, Faster R-CNN achieves a remarkable balance between precision and speed, rendering it particularly well-suited for real-time applications where rapid detection is imperative. This versatility makes it an invaluable tool in numerous domains, including surveillance, autonomous driving, and industrial inspection. In the specific context of the Automatic Helmet Violation Detection system, Faster R-CNN proves its mettle by efficiently detecting and classifying motorcycle helmets within surveillance videos. This application underscores the model's ability to overcome various challenges, such as limited resolution, adverse weather conditions, and occlusions, thereby showcasing its robustness in practical scenarios.

- *Libraries*

- Pandas is a powerful Python library designed for effi- cient data manipulation and analysis. It is particularly well-suited for handling large datasets, and it incorpo- rates the capabilities of NumPy. Pandas is instrumental in performing extensive calculations and operations on structured data.
- NumPy is a versatile array processing library that en- hances the performance of complex array objects in Python. It is an essential package for scientific com- puting, providing support for large, multidimensional arrays and matrices. NumPy is crucial for high-level mathematical functions and operations on these arrays. on these clusters.
- Matplotlib is a 2D plotting library for Python, enabling the creation of high-quality visualizations for various print and web formats. With Matplotlib, users can gen- erate a wide range of statistical plots, including line charts, histograms, power spectra, bar plots, contour plots, scatterplots, and more.
- A complete Python machine learning library is called Scikit-learn. It includes numerous techniques for group- ing, regression, classification, and other purposes. Nu- merous statistical and machine learning models, includ- ing DBSCAN, k-means clustering, decision trees, and support vector machines, are supported by Scikit-learn. It combines with SciPy and NumPy with ease.
- Google created the open-source machine learning frame- work TensorFlow. It offers a strong and adaptable platform for building, honing, and implementing deep learning and machine learning models. TensorFlow is a distributed computing framework that leverages compu- tational graphs and can be used for a variety of purposes, such as recommendation systems, speech recognition, picture recognition, and natural language processing. TensorFlow is a popular tool among data scientists, engineers, and academics because it provides great per- formance, flexibility, and a vast ecosystem of tools and resources.

V. IMPLEMENTATION AND RESULTS

The proposed Automatic Helmet Violation Detection system leverages deep learning methods, particularly the Faster RCNN model, to address challenges in real-time surveillance film, specifically focusing on the identification of motorcyclists wearing helmets. The issues faced by existing models, such as limited resolution, inadequate lighting, adverse weather, and occlusion, are targeted by a unique approach. The method- ology involves training the Region Proposal Network (RPN) first, using the RPN weights to then train the Faster R-CNN model. The objective is to enhance the accuracy of helmet detection in live surveillance footage.

In terms of experimental results, the system exhibits promis- ing outcomes, achieving a commendable accuracy rate in iden- tifying motorcycle helmets in real-time surveillance scenarios. This success underscores the capability of machine learning methodologies in automatic helmet detection for motorcyclists, emphasizing the effectiveness of the proposed strategy in overcoming challenges faced by current models.

The work emphasizes the critical role of technology in addressing the rising issue of motorcycle accidents, particu- larly due to non-compliance with helmet laws. With a focus on countries like India, where motorcycle usage is high, the implementation of a computer vision-based automated system for helmet detection is seen as a cost-effective solution. The system's integration with existing video surveillance infras- tructure is highlighted, emphasizing its potential to alleviatethe workload of traffic police and improve overall road safety.The primary goal of the study is to prevent significant injuries resulting from motorcycle accidents by deploying computer vision-based automatic helmet recognition. The proposed solution aims to identify riders violating helmet laws in real-time and alert authorities for appropriate action. This technology is positioned as a vital tool in promoting compliance with helmet laws and contributing to overall road safety.

In summary, the increasing number of motorcycle accidentsand head injuries among riders underscores the importance of implementing measures to encourage helmet usage. The proposed solution, utilizing computer vision-based automated helmet detection technology, is positioned as an effective approach, especially in regions with high motorcycle usage. The primary goal remains the prevention of significant injuries caused by traffic accidents by promoting compliance with helmet laws through automatic

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helmet detection systems.

The Faster R-CNN architecture is chosen for helmet de- tection, with transfer learning using pre-trained weights from the COCO dataset. Performance indicators like accuracy, pre- cision, recall, and F1-score are used in the assessment. Also, live surveillance testing is conducted to assess the model's accuracy in identifying helmet violations under challenging conditions.

The inclusion of the COCO dataset is highlighted as a valuable resource for training the system, providing a diverse set of images with detailed annotations. The Faster R-CNN model's effectiveness in object recognition tasks, coupled with the Region Proposal Network, is emphasized for real- time applications, particularly in the context of the Automatic Helmet Violation Detection system.

The implementation of the proposed system involves the utilization of key libraries such as Pandas, NumPy, Matplotlib, Scikit-learn, and TensorFlow. These libraries contribute to data manipulation, analysis, visualization, and machine learning functionalities. TensorFlow, in particular, serves as the core machine learning framework for building, training, and de- ploying the Faster R-CNN model.

In conclusion, the research presents a comprehensive ap- proach to addressing the critical issue of helmet violation de- tection among motorcyclists using advanced computer vision techniques. The combination of deep learning methodologies, model selection, and rigorous evaluation demonstrates the potential impact of the proposed system on improving road safety by promoting helmet compliance.

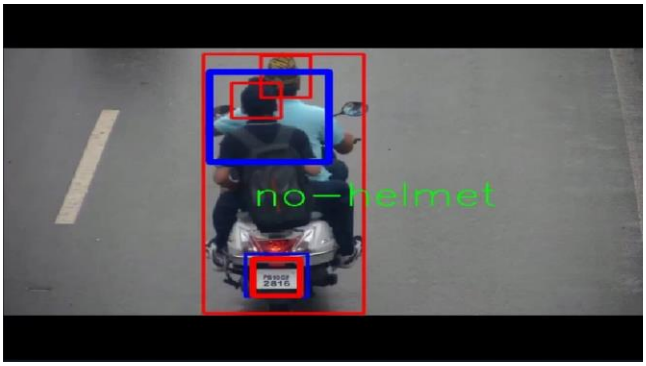

Fig 2 Helmet Detection-1

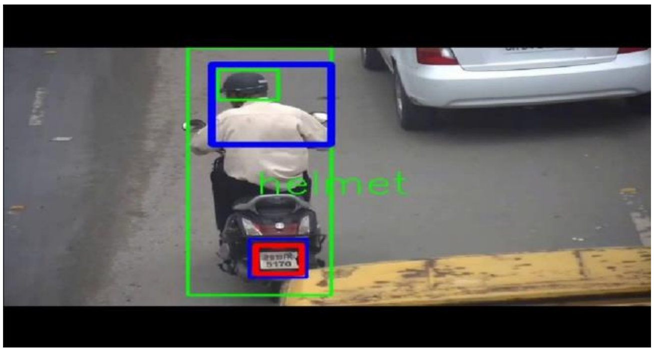

Fig 3 Helmet Detection-2

VI. CONCLUSION

In conclusion, the Automatic Helmet Violation Detection system offers a highly effective solution to enhance road safety, particularly in regions with high motorcycle usage. The proposed methodology, leveraging deep learning techniques and the Faster R-CNN model, demonstrates promising results, achieving a high accuracy rate in real-time surveillance scenar- ios. This research addresses the pressing issue of motorcycle accidents by providing a cost-effective, automated system to enforce and promote helmet laws.

The significance of the project lies in its potential to reduce the workload of traffic police through a proactive approach to helmet compliance. The real-time detection and immediate alerting of authorities contribute to improving overall road safety and preventing significant injuries resulting from traffic accidents. The study provides a comprehensive overview of helmet detection methodologies, showcasing the evolution from traditional computer vision to advanced deep learning models.

By incorporating the COCO dataset and utilizing key libraries such as Pandas, NumPy, Matplotlib, Scikit-learn, and TensorFlow, the research demonstrates a well-rounded implementation strategy. The proposed system's reliance on TensorFlow underscores its scalability and applicability. In summary, the Automatic Helmet Violation Detection system emerges as a promising technological intervention, offering a viable solution to encourage helmet compliance and reduce head injuries among motorcyclists.

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