Deep Learning-Based System for Automatically Detecting and Panelizing Helmet Rule Violations

V.D. Vaidya[1], Sinare Sakshi Sandeep[2], Roy Mahi Dharmendrakumar[3], Mundhe Shreya Ramesh[3]

[1]*HOD, Dept. of Cloud computing and big data, P.Dr.V.V.P. Institute of Technology and Engineering, Loni, Maharashtra, India*

[2,3,4] *Final year Diploma Student, P.Dr.V.V.P. Institute of Technology and Engineering, Loni, Maharashtra, India*

---***---

ABSTRACT - In order to reduce the likelihood of brain damage sustained while motorcycling, a helmet should be worn at all times. Even in jurisdictions where it is the law, fewer people are opting to wear helmets. This system's goal is to automate the process of recognizing motorcycle license plates and riders, whether they are wearing helmets or not. Currently, helmets worn by motorcyclists are physically examined by law enforcement. Due to human error and the slow rate of manual assessment, there are too many limits to justify it. Due to the lack of complete automation in CCTV-based systems, human interaction in monitoring is still necessary in many non- and semi-urban settings. Due to the increasing number of fatalities caused by motorcyclists who did not wear helmets, there has been an increase in research on the topic of road safety monitoring. To achieve the goal of automatic helmet recognition and analysis of the number plate of the helmet regulation infringement, this strategy proposes using YOLO V8 and decision trees to construct an effective image processing solution. Extensive measures have been used to test the effectiveness of this technique, and the findings have been quite good.

Key Words: K- nearest Neighbor classification, Regression analysis, Hidden Markov model, Decision Tree.

1.INTRODUCTION

Motorcycle riders must wear helmets to protect their health. Rider and passenger survivability in an accident is greatly improved by wearing a helmet. Motorcycle riders must wear helmets in several places. However, many motorcyclists ride unprotected. The police officer tried but failed to restore control by force.

Motorcycles dominate motorized mobility in many developing nations. Attempts have been made to employ machine learning to detect helmeted bikers. Policing and public awareness initiatives require accurate and up-to-date data on motorcyclist helmet use on public roadways. Scene object detection has been a current topic for computer vision researchers. Using object recognition, scene items may be accurately categorized and found. It can detect multiple stimuli due to its sensitivity. Researchers have long studied how to securely integrate item identifying systems into industrial operations. Motorcyclists' most important PPE is a helmet, which can save lives and brains. Visual inspections are the main way transportation law enforcement verifies driver compliance. However, traffic film analysis is becoming more important in highway surveillance networks that can detect security-critical acts. Collisions and traffic signal infractions can be monitored alongside volume and speed. Computer vision studies have found more complicated driving behaviors such illegal lane splitting and mobile phone use.

Many cars now have helmet detection systems. Motorcycles are the main form of transportation for many developing countries' workers. increased biker numbers correlate with increased motorcycle accident fatalities. Motorcycle accident fatalities can be reduced in several ways. Always wear a helmet when riding a motorcycle. If riders had to wear protective gear, motorcycle accident deaths would drop significantly. Despite legal requirements, many riders don't wear helmets. Motorcyclists make it hard for police to maintain order. Manually monitoring every motorcycle would be costly and time-consuming. Many drivers don't wear helmets despite legislation in numerous states. In developing nations, motorcycle fatalities have been rising for decades despite the widespread availability of helmets for riders and motorists. Though helmets are readily available, this issue remains. Motorcyclists and bikers could avert many injuries and deaths by wearing protective headgear. A helmetless motorcyclist's head is more susceptible to serious damage or death. Without helmets, motorcyclists risk brain damage and higher hospital and social costs.Many studies show that a pulse rate sensor can identify if a rider is wearing a helmet. Pulse rate monitors are harder to manipulate than microswitches and infrared detectors. This campaign fulfilled its goals with little investment. Road drivers must wear helmets for this reason. The result is fewer traffic deaths. You can follow this approach without a cell phone. Large text blocks seem better on OLED screens due to their reduced size and legibility. By monitoring the road for approaching vehicles, drivers dramatically reduce their collision risk. precise after returning to pre-training weights. The writers will also collect a lot of data, both good and negative real-life instances, to improve the network's generalization.

[1] Wei Jia et al. authors present a solution for the end-to-end detection of motorcycle helmets using the YOLOv5 algorithm, which operates in real-time. This system can automatically identify motorbikes in photos or videos and determine if the rider is protecting their head with a helmet. In order to obtain a high level of accuracy in real time, our method is divided into two stages: motorcyle detection and helmet detection. The authors train YOLOv5-MD and YOLOv5-HD models for each stage. The fact that our models are still quite small—just 20.6 MB for the first stage and 14.8 MB for the second—is another great thing. The authors also suggest HFUT-MH, a new dataset of motorbike helmets collected from various traffic scenes in China under varying occlusion and lighting conditions, as a means of testing our method's efficacy. We achieved high accuracy and real-time effect with our dataset, which included an end-to-end motor cycle helmet detection mAP of 97.7 percent, an F1-score of 92.7 percent, and a detection speed of 63 frames per second. By adding up the helmet count and No_helmets, our algorithm can also tell you if the motorbike is too crowded. To minimize recurrent detection—a crucial component of real-world traffic video surveillance—the authors may incorporate a tracking algorithm into it in the future. This would allow it to detect objects only once. [2] Xu He et al. publication provides a detailed description of the Yolov5-based safety helmet and overalls detection technology. Training and optimizing models are part of it, as is the building of a set of procedures to swiftly acquire datasets according to experiment demands. The results show that the detection accuracy and recall rate may be improved by adding more categories. It is possible to further decrease the target's missed detection and false detection rates with the later algorithm design. Adding a coordinate attention technique to the yolov5 network's backbone after dataset optimization, this paper shows that the detection impact may be improved without adding computation.[3] Yusong Lin et al. Although current intelligent video monitoring technology can roughly detect helmets, the complex environment of a construction site, along with differences in scale, makes the algorithms unsuitable and results in low detection accuracy and precision. Using the concept of super resolution, this study presents a new algorithm for helmet wearing detection that addresses the challenges and problems associated with the current methods. These challenges include small scale, high similarity in appearance, and complicated background interference. Furthermore, our own dataset of real-life scenes serves as experimental proof of the method's efficacy.

This paper's second portion provides an analysis of the previous studies that were considered as Litereature Survey. In Section 3, the course of action is described in full detail as Proposed methodology. Part 4 digs into the experimental evaluation, while Section 5 explores potential changes before wrapping up the article with a conclusion on the current proposal.

2. LITERATURE SURVEY

[4] Tasbeeha Waris et al. One difficult ITS application is the automatic detection of helmet violations from real-time videos of bikers. With it, it's easy to identify helmet-less bikers and give them a ticket. This study suggests a method for ITS that can detect helmet violations automatically. The suggested method exploits a Faster R-CNN deep learning model to identify helmet violations in traffic videos and take appropriate action against those responsible. The suggested method attained a 97.6% success rate, according to the experimental results. This work has the potential to be expanded in the future to include more capabilities, such as the ability to detect number plates and other traffic offenses.

[5] Ahatsham Hayat et al. studied helmet identification as a computer vision problem and offered a deep learning-based solution. Worker safety is a serious concern on construction sites. Previous research has had difficulty spotting items in low-light photos and in particular smaller objects (because of the greater distance between the camera and the workers). To that end, we suggested an architecture based on YOLOv5x to recognize safety helmets automatically on building sites. Due to its demonstrated accuracy in object detection tasks, this work utilized various variants of the YOLO architecture, including YOLOv3, YOLOv4, and YOLOv5x, to

recognize safety helmets. When it came to identifying safety helmets, YOLOv5x stood out with the highest mAP (92.44%), demonstrating its effectiveness even in low-light photos and when dealing with smaller items. Although YOLOv5x-based design has significantly improved outcomes, it does have some drawbacks. For example, when faced with an obstruction or things that were visually similar to helmets, the suggested deep learning model had difficulty performing. Including more photos in the model's training set, such as those from the aforementioned scenarios, may improve its performance. Workers could be even safer in the future with the addition of additional detecting safety gear like vests, gloves, and goggles.

[6] Jun Liu et al. Adding SPD, ASPP, and BiFPN to YOLOv5 is the authors' main goal; they improve upon YOLOv5 by 1%. SPD enables the network to take more precise samples while also improving data preservation. Since the cavity convolution method keeps more useful data, ASPP forgoes the receptive field concept. By supplying the deeper layers of the neural network with more semantic information, BiFPN prevents the loss of effective feature information. We have improved the efficiency of helmet detection by expanding our dataset to include more scenarios, focusing on small targets and dense helmet images, and using higher criteria for factors like weather, occlusion, lighting, viewing angle, and background interference. We will be able to recognize safety helmets more precisely from a variety of angles and improve the network's ability to acquire features of small targets in our next step of development. Concurrently, the authors will execute real-world applications and establish a system to track whether employees enter the work area wearing safety helmets, thereby decreasing the frequency of accidents and economic property loss.

[7] Chentao Shen et al. authors suggest a novel approach to intelligent surveillance that makes use of YOLOv5 networks for small-scale helmet detection. The authors improve weak-feature helmet detection by using foreground masks and automatic information weight allocation through the channel-space attention module. Improving small helmet identification is possible with the addition of a smaller-channel channel. The experimental results show that the enhanced network can successfully recognize miniature helmets. For real-world applications, it is crucial to expand the dataset and enhance our approach even further. To make the method more adaptable to smart industrial systems and improve human-computer interaction, our future work will centre on improving the dataset, adding more techniques, and testing it on other weak-feature object detection tasks.

[8] Cong Liu et al. Helmet detection tasks are notoriously challenging in high-risk environments like construction sites owing to a conglomeration of factors like dense personnel, objects obstructing targets, and tiny pixel points. Other issues include difficulties in detecting small targets and a large number of detection model parameters. In order to tackle these issues, we propose an improved model that is based on YOLOv7-Tiny. This model will improve the feature extraction network, which will increase its capability for small targets. We also introduce a coordinate attention mechanism to help the network focus even more on coordinate detail information. Lastly, we suggest an H-Dense feature fusion network, which will improve the information exchange in the multi-scale feature extraction network, increase network detection performance, and reduce the model's parameter count. The experimental results reveal that the mAP is 1.5% higher with the revised YOLOv7-tiny algorithm than with the original network, all while the number of parameters is reduced by 21.9%. In the test set, with only 4.7M parameters, the enhanced YOLO model achieves a mAP value of 94.9%. In complicated situations, it satisfies the need for helmet detection.

[9] Benqi Liao et al. authors suggest enhancing the YOLOv5 helmet-wearing detection model to address the drawbacks of manual supervision of operators in complex environments, as well as the issues with low detection accuracy and inefficiency of current detection methods. The model boasts an average detection accuracy of 94.8%, a detection speed of 42FPS, and a size of only 1.7MB, more than making up for the time-consuming and laborious on-site supervision. This approach has some relevance in production guidance and makes up for the shortcomings of labor-intensive and time-consuming on-site supervision. The next step in minimizing the likelihood of accidents in the production process will be the development of a real-time warning system that operators can use to be reminded to wear helmets at the appropriate times.

[10] Adithya Krishna R et al. An impressive 98% accuracy and 99% precision were displayed by our model. The model's viability and its effectiveness in a real-world setting are demonstrated by these statistics. Also, our law enforcement system can benefit from this system's scalability, which will improve the road transport environment. So far, our system has only

addressed a subset of the several unresolved issues with our current setup. We can automate the identification of additional violations in our environment with our endless alternatives, and there is always room for improvement. To better inform the model about the impact of climate change on road transport, more effective auxiliary devices are available, such as heat-image sensors and weather detection systems. It is more effective to adapt to every possible situation.

[11] Aiguo Li et al. this research presents a YOLOv8n-based helmet target detection system that is both efficient and effective. In order to address the issues of a small or easily obstructed helmet target, a high false detection rate, and a missed detection rate, this research suggests a PC-BiFPN structure. This structure incorporates the improved GAM attention mechanism based on Tanh into the network. If we can get the accuracy up, we can make the model more reliable, and it will be able to recognize smaller and more obscured targets.With the updated model, the S-CSHD dataset saw a 1.1% improvement in mAP, a 1.1% improvement in P, and a 1.1% growth in R. Workers' helmet use may be accurately detected using the suggested method, according to the results. With its many improvements over competing target detection techniques, it makes it possible to automatically identify if construction workers are wearing helmets.

[12] Jingwen Su et al. Based on YOLO v5, the authors present a new algorithm that can determine when someone is wearing a safety helmet. In the first place, the authors use a spatial pyramid structure that has faster processing and fewer parameters to speed up the network's inference. In the second place, they employ delayed convolution to collect richer feature information. The second step in expanding the network's sensory field is the addition of a FAM module to the network's neck architectural component. By incorporating a 160x160 detection layer into the initial three-head network of detecting heads and utilizing soft-NMS to eliminate unnecessary prediction bounding boxes, the authors improved the network's ability to handle occluded targets in complex backgrounds. By comparing it to other popular algorithms, the experimental results show that the upgraded YOLO v5 is the best at identifying when a person is wearing a safety helmet. Eventually, the writers will look at the potential of constantly monitoring whether or not site workers are wearing safety helmets.

[13] Zhongyan Sui et al. writers suggest a novel two-branch design for safety helmet identification. To improve the accuracy of subsequent detection, the input image is first improved using SRGAN to attain high perceptual quality and rich detail. After that, the authors modify the YOLOv5 network architecture so that it has two branches: one for detecting the head-shoulder and another for generating proposal boxes. The authors also present a new method for fusing data. Authors execute dynamic adaptive weight adjustment depending on each branch's learning performance during training after IoU matching of proposal boxes from the two branches. On the CUMT-Helmet dataset, our novel approach outperforms current state-of-the-art object detectors, especially in difficult situations with low visibility and clutter.

[14] SHAOHUI ZHONG et al.suggests a multi-threaded logic (MTL) architecture that incorporates license plate region recognition, allowing for the simultaneous detection of helmet wearing, carrying passengers, and license plate identification. Adaptability to complicated situations and performance in recognizing small objects are both improved by integrating the Transformer architecture into the model, which in turn boosts YOLO's feature representation capacity. Furthermore, multi-scale object detection capabilities are significantly improved with the advent of the FPN. Multiple metrics indicate that the suggested model outperforms YOLOv8. For the Ebike, Plate, and Helmet tasks, the model outperforms YOLOv8 with an accuracy of 96.1%, 92.9%, 84.6%, and 67.9%, respectively, when it comes to object detection. The suggested model outperforms YOLOv8 by a small margin (83.8% vs. 84.3% in terms of mAP0.5). The overall performance within the MTL framework is superior, as shown by improvements in other key metrics, even though the improvement in mAP0.5 is not significant. By reducing the number of parameters by 4.3%, F-YOLOv8 improves the model's efficiency and effectively decreases the storage requirements of the model. This leads to a significant improvement in FPS, reaching 80% of YOLOv8's performance, with higher detection times, even though GFLOPs increase by 44.4%. Also, F-YOLOv8 is better at detecting small objects and adapting to complicated situations than other multi-task detection models. This makes it a better fit for edge computing devices with limited resources, and it has a lot of potential uses in intelligent transportation, security monitoring, and other areas.

3. METHODOLOGY

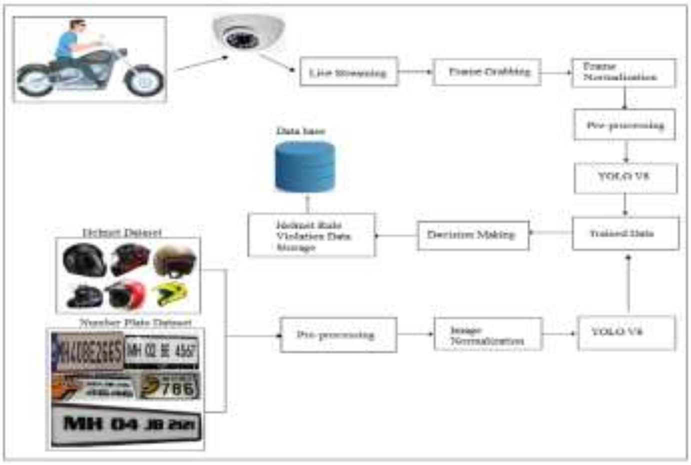

Figure 1: Proposed model System Overview

In figure 1 above, we can see the proposed method for effectively realizing the helmet rule breach with Yolov8. The following part provides a detailed explanation of the numerous processes that are accomplished in the offered approach.

Data Input and Admin or User Login—The offered method starts with the use of admin or user logins. An interactive java-based GUI built on the swinging platform is accessible to both the administrator and the user. The admin uses the user-friendly GUI to complete the registration process by entering valid details like username, DOB, mobile number, email ID, etc. Once the registration is complete, the administrator can access the system with the credentials given during registration. Managing user access is within the purview of the admin who logs into the system.

The user can also access the system effectively through the interactive user interface that was designed utilizing the swing platform. Through its own secure login, the administrator controls the user's accessibility. An image or video can be uploaded by the user to help with the helmet rule violation identification.

A user-provided video or image serves as the input data. You can use the image for the evaluation right away, but you'll need to successfully transform the video into a series of frames. The input media files are saved in a given directory or path. This is accomplished by starting a thread in Python that will monitor the specified directory or path for any media files that are input. The following steps illustrate the procedure that the helmet rule violation system goes through after it detects an image or video in the location.

The second step is to detect the motorcycle, which involves the system using the image to successfully identify the motorcycle. Identifying the motorbike in the image is the initial stage in the process of detecting a helmet law violation. When it comes to motorbike object recognition, the Yolov8 method is what the identification module relies on. Prior to using this model for motorcycle recognition, it must be trained Installation of the Yolov8 model's ultralytics and download of the roboflow dataset are the first steps in the training process. You may access the motorbike recognition dataset at this URL: https://universe.roboflow.com/mrncap/motorcycle-rider/dataset/2. Then, you can join roboflow with an API key. In order to retrieve a directory listing of files, the received dataset is efficiently examined. Next, the amount of files in the directory can be extracted using the file list. Of the total 2607 files, 248 are designated for training purposes. After the files are sorted alphabetically, they are jumbled by transferring all 323 of them to the final destination. After recalculating the directory count, we find that there are 571 files in the training directory and 2284 files in the other directory.

After the roboflow data has been successfully integrated and the motorcycle dataset has been effectively shuffled, the yolov8 model may be started for the yolo object identification challenge. With a batch size of 32 and an image size of 640, the detection model is trained for 50 epochs using the trained weights. Once the yolov8 model has been trained, the project runs are saved in the designated directory as a zip file. Table 1 provides a description of the Yolov8 model.

S. no	Layer Type	Parameters
1	Convolutional Layer	7x7x64 Stride-2
2	Maxpool Layer	2x2 Stride 2
3	Convolutional Layer	3x3x192
4	Maxpool Layer	2x2 Stride 2
5	Convolutional Layer	1x1x128
6	Convolutional Layer	3x3x256
7	Convolutional Layer	1x1x256
8	Convolutional Layer	3x3x512
9	Maxpool Layer	2x2 Stride 2
10	Convolutional Layer	1x1x256
11	Convolutional Layer	3x3x512
12	Convolutional Layer	1x1x256
13	Convolutional Layer	3x3x512
14	Convolutional Layer	1x1x256
15	Convolutional Layer	3x3x512
16	Convolutional Layer	1x1x256
17	Convolutional Layer	3x3x512
18	Convolutional Layer	1x1x512
19	Convolutional Layer	3x3x1024
20	Maxpool Layer	2x2 Stride 2
21	Convolutional Layer	1x1x512
22	Convolutional Layer	3x3x1024
23	Convolutional Layer	1x1x512
24	Convolutional Layer	3x3x1024
25	Convolutional Layer	3x3x1024
26	Convolutional Layer	3x3x1024 Stride 2
27	Convolutional Layer	3x3x1024
28	Convolutional Layer	3x3x1024
29	Fully Connected Layer	
30	Fully Connected Layer	

Figure 2: Model Summary for YOLOv8

A Convolutional Neural Network (CNN) variant, the YOLOv8 is its offspring. To improve the accuracy of object recognition, it employs the CNN approach's components in a novel and efficient way. To prevent overfitting and regularize the model, the Yolo design uses 24 convolutional layers with different parameters, a max pooling layer, and a number of dropout and batch normalizations. Two fully connected layers are the model's apex.

The channels are max-pooled after the first convolutional layers decompose and reduce them; the kernel size is 2x2 and the stride is 2. Every layer of this model uses the same max pooling layers. With each succeeding convolutional layer, the kernel size increases to handle the influx of new data. All of these layers are activated using the ReLU activation mechanism. With the exception of the fully connected layers, which use a linear activation function, every layer has the same activation function.

The next stage in identifying the rider and helmet in order to resolve the helmet regulation infringement occurs once the motorcycle has been recognized. In the following phase of the process, this phase is thoroughly explained.

Next, we go on to Step 3 of the process: helmet detection. Once the motorcycle has been identified in the image, we crop the area around it and feed it into this step of the technique. The technique uses the image to correctly detect the helmet in the photo. Using the Yolov8 approach, which effectively recognizes both the rider and the helmet as objects, the helmet identification module does its job. It is necessary to train this model before applying it to helmet recognition.

To begin training for helmet identification, you must first install ultralytics in order to run the Yolov8 model, and then acquire the roboflow dataset. After connecting roboflow with an API token, you may access the helmet recognition dataset at this URL: https://universe.roboflow.com/srp/helmet-detection-aiauu/dataset/3/download/yolov8.

To get a list of the files in the subdirectory, an effective scan is performed on the received dataset. After that, we can use the file list to find out how many files are in the folder. For training reasons, there are 256 files, for a grand total of 11934 files. Following their transfer to the destination directory, the 700 files will be alphabetized before being randomly shuffled. The number of files in the directory has been recalculated and comes out to 2,348 for the training directory and 9,752 for the extra directory.

Following the successful integration of the roboflow dataset and the effective shuffling of the motorbike dataset, the yolov8 model can be initiated for the yolo task—object identification. Starting with the learnt weights, the detection algorithm was trained on a dataset with 416 images and 32 batches across 50 epochs. Following the completion of the yolov8 model's training, the project runs are archived in the specified place as a zip file. Since the helmet regulation is being observed, no action will be taken after the helmet detection if the cyclist is detected wearing a helmet. If the helmet is not recognized and a helmet regulation violation occurs, the following step is to identify the vehicle number.

The fourth step of the process is to detect vehicle registration plates. After the system for detecting motorcycle helmet rule violations is identified in the image, the clipped motorcycle region is used for this purpose. The approach makes use of image analysis tools to positively identify the license plate shown in the photo. The number plate recognition module successfully recognizes number plates as objects by utilizing the Yolov8 approach. Important training of this model is required before it can be used for license plate identification. At the outset of the training process, you'll need to install ultralytics to run the Yolov8 model and get the roboflow dataset to train helmet identification. Use of an API key associated with roboflow allows access to the dataset utilized for car registration plate recognition, which can be found at https://universe.roboflow.com/augmented-startups/vehicle-registration-plates-trudk/dataset/1.

After the Roboflow dataset was successfully integrated, the YOLOv8 model was used to complete the YOLO job of detecting car registration plates. Using the learned weights, we trained the dataset for 50 epochs with 416 images and 32 batches to implement the detection algorithm. After the yolov8 model training is finished, the project runs that are produced are saved in the chosen directory as a compressed file. After the helmet rule violation's license plate has been located, it is cropped and sent on to the next stage so that it may be read. This is accomplished by means of the EasyOCR module for Python. Once this library receives the cropped car registration plate, it returns the identify of the helmet rule violation individual. The system then stores this information and displays it to the user through the user interface.

4. RESULTS AND DISCUSSIONS

Using the programming languages Python and Java, the offered method for detecting helmet rule violations was created. A standard Windows laptop with an Intel Core i5 processor, 8 GB of RAM, and a 1 TB hard drive was used to conduct the research. To carry out the idea, two separate Integrated Development Environments (IDEs) were used: NetBeans for Java and Spyder for Python.

A more precise method of automatically detecting infractions of helmet regulations is the target of this study. Then, we will put the trained model to the test to see how well it can detect helmet rule violations using an appropriate performance assessment approach. There will be an assessment like this after the first phase ends.

The component in charge of identifying violations of the helmet regulation must have its level of precision studied. This must be accomplished in order to ascertain the efficacy of the suggested method. One possible metric for the procedure's accuracy could be the quantity of inaccuracy it produces. The strategy's reliability increases significantly as the degree of mistake decreases. We have the root mean square error metric at our disposal, which is a handy tool for investigating the reliability of this model's execution.

Performance through Root Mean Square Error Evaluation

One way to assess the potential inaccuracy among several consistent and interdependent qualities is with the use of the Root Mean Square inaccuracy (RMSE), sometimes called the best performance statistic. The accuracy and incorrectness of identifying helmet regulation infractions will be used to assess the pros and limitations of the proposed methodology, respectively. We will use violations of helmet restrictions to weigh the pros and cons of the strategy. Equation 1, given with more detail in the section that follows, can be used to calculate the root mean square error (RMSE).

$$\mathrm{RMSE}_{fo} = [\sum_{i=1}^{N} (z_{f_i} - z_{o_i})^2 / N]^{1/2}$$

Where,

$\sum$ - Summation

$(Zfi - Zoi)^2$ - Differences Squared for the helmet rule violations recognized properly and helmet rule violations recognized improperly

N - Number of conducted Experiments.

We used the specified methodology to calculate the root mean square error (RMSE) for several rounds of the helmet rule violation detection process. Aiming to assess the methodology's accuracy, the iterations were carried out.

After 10 iterations, the method's efficacy was assessed. The suggested methodology consistently produces consistent identification results after each successful execution, independent of the frequency of its application. After this process is finished, the results will be used to achieve the purpose of running an RMSE analysis. After calculating the values shown in Table 1, which may be seen below, the RMSE readings have been determined.

S no.	Number of Iterations	Correctly Recognized Helmet Rule Violation	Incorrectly Recognized Helmet Rule Violation	MSE
1	10	10	0	0
2	10	8	2	4
3	10	8	2	4
4	10	7	3	9
5	10	10	0	0

Table 1: RMSE outcomes for 5 hand gesture recognition.

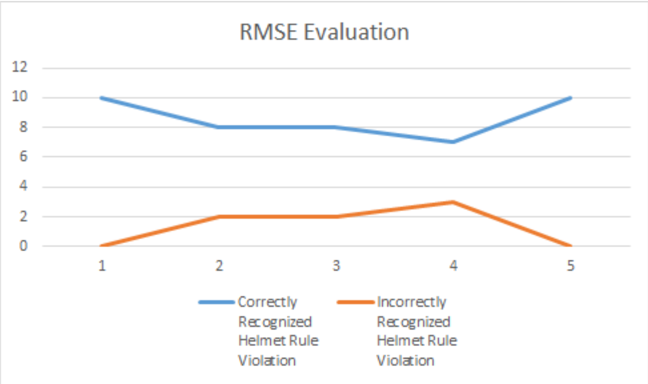

Figure 3: Line Graph for RMSE outcomes for 5 hand gesture recognition.

As a foundation for utilizing the identification effectiveness results, we are using the RMSE observations reported in Table 1. Figure 3 is a graphical representation based on the tabular data provided here. There is a very little margin of error when using the suggested methodology to detect cases of non-compliance with helmet requirements, as seen in the table and graph that follow. One possible explanation for the increased identification accuracy is the use of a proposed method that makes use of deep learning using Yolov8, leading to a considerable improvement in recognition accuracy. The analysis found that there is an RMSE of 1.843 when it comes to identifying helmet rule infractions. For preliminary studies, this result stands out. As a result, you must check if the effort has been proven to be successful.

5. CONCLUSION AND FUTURESCOPE

Lots of drivers still don't wear helmets, even though regulations mandating their use were just passed. More and more people are dying on motorbikes every year, especially in poorer nations, even though helmets are easily accessible to both riders and drivers. And this is happening even if there is no shortage of helmets. Many preventable head injuries and deaths might be prevented if motorcyclists and bicyclists were simply required to wear protective headgear. Without proper protection, a motorcyclist's head is much more likely to sustain serious injuries or even death. Not only do motorcyclists who don't wear helmets put a costly burden on hospitals, but those who suffer brain damage also confront social and financial costs. Consequently, this proposed method seeks to create an efficient image processing strategy by means of the YOLOv8 model in order to achieve the objectives of automated helmet identification and analysis of the license plate of the helmet regulation compliance. Future enhancements to the suggested system could involve combining it with automated e-challan platforms and real-time traffic surveillance systems, allowing for large-scale enforcement. A scalable and effective approach to increase road safety and helmet compliance might be achieved by further enhancing accuracy under demanding situations and deploying on edge devices for faster processing. The system could then be expanded to detect more traffic offenses.

Future scope: To make it even more accurate in different traffic and environmental situations, the Automatic Helmet Rule Violation Detection and Penalizing System can use advanced deep learning models. Potentially integrated with government databases and featuring automatic license plate recognition for real-time fine production are features that could be included in future versions. Multiple traffic offenses, including cell phone use, signal jumping, and triple riding, can be detected by expanding the system. Enhancing road safety and smart city projects, the system can be enhanced with edge computing, IoT, and cloud analytics to allow for real-time monitoring, speedier enforcement, and large-scale implementation.

REFERENCES

[1] W. Jia, S. Xu, Z. Liang, Y. Zhao, H. Min, S. Li, and Y. Yu, "Real-time automatic helmet detection of motorcyclists in urban traffic using improved YOLOv5 detector," IET Image Processing, 2021, doi: 10.1049/ipr2.12295.

[2] X. He, Z. Lan, C. Peng, and Y. Gou, "A safety helmets and overalls detection algorithm based on improved YOLOv5," in Proc. 6th Int. Conf. Electronic Information Technology and Computer Engineering (EITCE '22), Oct. 2022, doi: 10.1145/3573428.3573727.

[3] Y. Lin, M. Liu, C. Yang, S. Li, and W. Zhang, "AC-YOLO: A safety helmet detection based on YOLOX," in Proc. 4th Int. Conf. Robotics, Intelligent Control and Artificial Intelligence (RICAI '22), Dec. 2022, doi: 10.1145/3584376.3584524.

[4] T. Waris, M. Asif, M. B. Ahmad, T. Mahmood, S. Zafar, M. Shah, and A. Ayaz, "CNN-based automatic helmet violation detection of motorcyclists for an intelligent transportation system," Computational Intelligence and Neuroscience, vol. 2022, Art. ID 8246776, Oct. 2022, doi: 10.1155/2022/8246776.

[5] T. Waris et al., "CNN-based automatic helmet violation detection of motorcyclists for an intelligent transportation system," Applied Sciences, vol. 12, no. 16, Art. no. 8268, 2022, doi: 10.3390/app12168268.

[6] J. Liu, J. Cao, and C. Zhou, "Helmet wear detection based on YOLOv5," in Proc. 2nd Asia Conf. Algorithms, Computing and Machine Learning (CACML '23), Mar. 2023, doi: 10.1145/3590003.3590017.

[7] C. Shen, Z. He, X. Zhao, and J. Zhang, "Small-scale helmet detection based on improved YOLOv5 and moving object detection," in Proc. ACM Symp. Spatial User Interaction (SUI '23), Oct. 2023, doi: 10.1145/3607822.3616411.

[8] C. Liu, Z. Hong, W. Yu, and D. Zhen, "An efficient helmet wearing detection method based on YOLOv7-Tiny," in Proc. 6th Int. Conf. Machine Learning and Machine Intelligence (MLMI '23), Oct. 2023, doi: 10.1145/3635638.3635652.

[9] B. Liao, T. Chen, and P. Xue, "Improved YOLOv5 algorithm for helmet wearing detection," in Proc. 4th Int. Conf. Artificial Intelligence and Computer Engineering (ICAICE '23), Nov. 2023, doi: 10.1145/3652628.3652672.

[10] A. K. R., S. P., and S. P., "Camera-mounted helmet detection with YOLOv8 on custom dataset," in Proc. 16th Int. Conf. Contemporary Computing (IC3 '24), Aug. 2024, doi: 10.1145/3675888.3676032.

[11] A. Li and L. Li, "Improved safety helmet target detection algorithm of YOLOv8n," in Proc. 14th Int. Conf. Communication and Network Security (ICCNS '24), Dec. 2024, doi: 10.1145/3711618.3711646.

[12] J. Su and Z. Gao, "Detection of safety helmet wearing based on improved YOLOv5," in Proc. 4th Int. Conf. Big Data, Artificial Intelligence and Risk Management (ICBAR '24), Nov. 2024, doi: 10.1145/3718751.3718904.

[13] Z. Sui, M. Pei, and Z. Nie, "Helmet detection in mines using two-branch YOLOv5 network with adaptive weight adjustment," in Proc. 7th Int. Conf. Sensors, Signal and Image Processing (SSIP '24), Nov. 2024, doi: 10.1145a/3725949.3725950.

[14] S. Zhong and X. Liu, "A safety detection method for electric bike riding incorporating license plate region recognition," IEEE Access, 2025, doi: 10.1109/ACCESS.2025.3588506.