International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

HELMET AND NUMBER PLATE DETECTION USING DEEP LEARNING

K. Keerthi[1], B. Guru Kavya[2], S. Sreelatha[3], S. Naseem Akthar[4]

Mrs. A. Aparna, M. Tech, Assistant Professor, Dept of CSE, CBIT
[1]UG Student, Department of Artificial Intelligence & Machine Learning, CBIT, Proddatur, YSR, A.P [2]UG Student, Department of Artificial Intelligence & Machine Learning, CBIT, Proddatur, YSR, A.P
[3]UG Student, Department of Artificial Intelligence & Machine Learning, CBIT, Proddatur, YSR, A.P [4]UG Student, Department of Artificial Intelligence & Machine Learning, CBIT, Proddatur, YSR, A.P
*Corresponding Author E-mail: aktharshaiknaseem@gmail.com

Abstract:

Violation of traffic rules and upsurge in road accidents are on the rise with the rising number of vehicles. The time required to monitor the use of helmets and check of the vehicle number plates is long and ineffective, especially when done manually. The name of the current project is Helmet and Number Plate Detection using Deep Learning, and presently the project is proposed to assist the traffic authorities with monitoring the rules related to road safety using the automated system. The system is trained to yield helmets and vehicle number plates by using YOLOv8 deep learning model on live video flows and images. Python development has been employed in the development of systems and computer vision methodologies in precise detection.

The web-based application will be realized using Flask that will provide the interface between the detection model and the user interface. The front end will be developed based on HTML, CSS, and JavaScript so that interaction will be easy and responsive. The system will be able to recognize helmet-less riders automatically and log the number plates of the contraveneing vehicles. This eliminates the necessity of constant person-to person supervision of workers and enhances efficacy in enforcement. The suggested system is scalable, versatile and can be accommodated into smart traffic management systems. All in all, the given project can be used to improve road safety with the help of the latest deep learning technologies.

Keywords:

Medical Chatbot, Mobile Application, health care, chat room

1. INTRODUCTION

Security in the construction project, industry and road transport systems has gained massive importance with the brisk urbanization, as well as, the significant increase in the number of vehicles on the roads. Traffic related accidents due to the lack of protective gears like helmets or as a result of breaking the traffic rules still pose a very severe danger to human lives. The traditional forms of manual surveillance are not always efficient, labor intensive and not applicable in large scale surveillance or real time surveillance. To compensate these drawbacks, investigators have progressively resorted to the application of computer vision and deep learningbased safety monitoring systems with automated methods.

The preliminary studies on helmet detection were aimed at detecting the safety helmet usage in the controlled construction setting through image processing and computer vision algorithms. As Ren et al. [1] showed, automated helmet detection systems should be used successfully to recognize non-helmeted workers, but they become weak in highly complicated backgrounds and high contrast lighting. As deep learning advanced, object detection models have been introduced that are more robust to enhance the accuracy and real-time performance in the problematic environments.

The recent researches have decided to incorporate the YOLO based architectures in order to engage the detection of the helmet in the complex industrial and power engineering settings. The paper by Jiatao et al. [2] suggested a better YOLOv7-based framework, which won't only enhance the rates of detections in cluttered scenes, whereas Gou et al. [3] prioritized the issues of dealing with occlusions, scale fluctuations, and the interference with the background in industrial environments. Additional gains included the incorporation of attention mechanisms reflecting in the works of Zhao [4] where Coordinate Attention was combined with YOLOv5s to enhance the detection of small and partly covered helmets without affecting the performance in real time.

Traffic surveillance systems have been modified to use helmet detection methods as well, especially to monitor the motorcycle riders. As put forward by Dasgupta et al. [5], a CNN-based method to determine helmet users amidst a group of riders was expected to be successful in enforcing the road safety about helmet usage, but it is also important to mention the problem of occlusion and low-resolution photos. These studies will focus on the need to have strong detection model, which can perform effectively in the real world traffic scenarios.

Along with the detection of helmets, Automatic Number Plate Recognition (ANPR) has become the important part of the intelligent traffic monitoring devices. Mipini and Giyane [6] studied the ANPR performance by region specific variables like plate type and the environment, whilst Shelke et al. [7] found multiple number plate recognition algorithms and wrong-way vehicle detection algorithms, noting that deep learning techniques are more accurate at the expense of more computation. The region-specific datasets suggested by Yaseen et al. [8] and Aung et al. [10] also proved that the systems tailored to the local plate design and languages have a significant effect on recognizing information.

Combined traffic enforcing systems of over-speed and a license plate have also been investigated. Dhonde et al. [9] introduced a real-time system that could detect violation of speed as well as identify vehicles, and this demonstrates how an intelligent surveillance system can apply practically in law enforcement.

Although great strides have been made, it is the contemporary literature that suggests that the problems of occlusion, complicated backgrounds, variation of illumination, and region-specific limitations remain the barriers to the improved work of the system. Thus, the necessity to find efficient, correct, and scalable safety monitoring systems that combine helmet detection and vehicle identification is high. The study is based on the previous literature [1-10], and the creation of smart vision-oriented system which could enhance the safety compliance and aid automated surveillance in real-world settings.

2. LITERATURE SURVEY

The use of computer vision and deep learning methods to enhance safety measurements in construction sites, industrial settings as well as traffic systems has been investigated by several researchers. This part is a literature review concerning the topic of helmet detections, YOLO-based object detection, and automatic number plate recognition.

The research conducted by Ren et al. [1] was aimed at the detection of safety helmets in a construction site based on a computer vision detection method that identifies the nondonned workers. Their algorithm was good to work under controlled conditions, but was not as much concerned with the difficulties of dynamic backgrounds and different lighting conditions, which asked to create more robust translation models.To eliminate these shortcomings, Jiatao et al. [2] suggested a better algorithm of helmet detection based on YOLOv7, which is designed to meet the requirements of power engineering settings. They also yielded better results using a mix of feature extraction and re-regression of bounding boxes, which led them to achieve high detection accuracy in cluttered scenes than the traditional YOLO-based models.

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

Gou et al. [3] proposed a method of helmet detection that is specially proposed to work in a complex industry environment in terms of occlusion and scale changes with background interference. The proposed method has a high degree of robustness and high real-time performance that is applicable in the industry and safety monitoring through object detection using deep learning formulas. Zhao [4] suggested further improvement of the detection accuracy by adding a Coordinate Attention (CA) mechanism to the YOLOv5s model. This method enhanced the feature representation and the detection of small and partially blocked helmets, and it was real-time efficient, this is why it was applicable to surveillance based in terms of safety.

Traffic surveillance systems have also been extended in terms of helmet detection. As proposed by Dasgupta et al. [5], a CNN-based method of monitoring helmet use among two or more motorcycle riders was created. Although the system worked well at enforcing the laws in the road, it was not effective at all images that were of low quality and high level of occlusion meaning that it was time to consider some higher level of detection measures.Another study in the field of traffic surveillance using ANPR technology appears in Mipini and Giyane [6], which compared the performance of multiple ANPR methods on the plates of Zimbabwean vehicles. They modulated the effects of local plate formats, variation of fonts and environmental conditions on the accuracy of systems as their study revealed the influence of region specific adaptations.

Shelke et al. [7] have outlined a survey of the number plate methods and wrong-way vehicle detectors. They compared the performance of the traditional image processing methods and deep learning based methods in their analysis and found that the deep learning based methods are more accurate and need more large datasets and more computational power.In order to address the problem of regions in ANPR systems, Yaseen et al. [8] created a new dataset specifically designed to suit the use of vehicles in northern Iraq. They demonstrated in their work that region-specific datasets are highly helpful in improving detection and recognition results because they deal with plate design variations, language, and illumination.

Dhonde et al. [9] have suggested a new system that incorporates vehicle over-speeding and automatic license plate recognition. Through image processing and speed estimation algorithms, the system was successful in detecting traffic offences in real-time which proves that the system can be used in intelligent traffic monitoring and law enforcement systems. Aung et al. [10] concentrated on the creation of ANPR system of Myanmar vehicle license plates. They dealt with the problems of plate structure uniqueness and local language character by providing a better accuracy rate with a tailored preprocessing and segmentation method.

The current system of traffic rule enforcement requires a significant part of the monitoring and detection of the violation to rely on the manual observation of the traffic police and surveillance personnel. The cameras of closed-circuit television (CCTV) are typically installed at the intersections of highways and places with a heavy traffic; yet, the footage analysis is carried out by humans. Violation in helmet use is determined visually by the officers and this leads to inconsistency and human error because of exhaustion, lack of concentration in attention and different judgment levels.

The identification of the number plate is either manual or semi-automated in the existing system whereby the officers are required to scan through the images or videos to retrieve the vehicle information. This is also cumbersome and very inefficient with the increase in traffic and especially in the highly populated cities.

Constant observation is not an easy task because of poor manpower and resources to carry out and it becomes hard to observe infractions once in a day.The current system also does not have the real-time detecting features that could make an immediate response against the violators of traffic. Slow response to the violation of suspects lessens the efficiency in implementing and could permit reiterations. Also, violation detection is significantly affected by human observation and therefore it may differ depending on the environmental circumstances like poor lighting, traffic surges and camera angles.The maintenance of records and violation tracking is in most cases done manually or in a piecemeal digital system, which makes the data management process tedious and full of errors. All in all, the current traffic enforcing system lacks automation, scalability, high operational costs and efficient proximity monitoring which explains the necessity of the intelligent and automated solution.

Weaknesses of the Current System.

- Human error and discrepancies in application of monitoring occur with manual monitoring.
- The violations that involve helmets and number plate are detected in a long time.
- Consumes a huge amount of manpower, which escalates the costs of operations and maintenance.
- Challenging to keep a constant check on high numbers of traffic.
- Absence of live detection and instant reaction asymmetrically followed.
- Poor violation records management and tracking.

The suggested system provides an algorithmic and self-driving answer to how and where to detect the usage of the helmet and vehicle number plates based on the principles of deep learning. It is built to address the limitations of the manual method of monitoring the traffic in that it provides real-time and precise monitoring of the vehicle that has committed a violation of rules. The system finds helmets and vehicle number plates with high accuracy and faster speeds using the YOLOv8 model of object detection of the images and video streams. The basic programming language is Python and the computer vision libraries to be used to provide quality image processing and execution of the model. Detection process is controlled by a Flask-based backend infrastructure that serves and processes user requests and the front-end interface created in HTML, CSS, and JavaScript offers an experience that can be used and responsive.

The proposed system will greatly decrease the human input in the process of detection and minimize the possibility of error due to manual observation and fatigue as the system will be automated. Real-time detection feature enables traffic violation violations to be detected much faster so that enforcement measures can be undertaken in time. The high accuracy of the YOLOv8 model can assure the stability of monitoring, even at a moving traffic of different density and conditions. Moreover, the system can process large amounts of traffic data effectively, and can therefore be deployed in the urban setting. The fact that manpower requirements are minimized contributes to the lower cost of operations, whereas, surveillance camera integration allows monitoring the operations around the clock which increases the general road safety and is useful in the implementation of smart traffic management solutions.

The system suggested has a variety of benefits as it automatizes the process of identifying helmets and number plates employing the technique of the deep learning method. It reduces human work, and error due to fatigue and subjectivity to a minimum by doing away with manual monitoring. An application of the YOLOv8 model allows detecting the number plates and helmets of vehicles in real-time and with high precision even in heavily populated areas. The system can effectively process high quantities of traffic data and as such it can be applied in cities and highways where traffic is very high. More rapid detection of traffic law violators encourages the implementation of enforcement measures in time, which raises the overall adherence to traffic regulations. The manpower requirement is also reduced thus reducing the cost of operations and maintaining consistency and reliability at the same time. In general, the given system is safer on the roads and contributes to the smart and scalable ways to manage traffic.

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

3. METHODOLOGY & MODULES

The suggested system starts with the stage of data collection when the images and videos of vehicles are collected using urban and highway cameras installed on the traffic. The dataset will be made to address a broad range of conditions, such as varying traffic volume, lighting conditions, and vehicle classes. This makes the detection model to be sound and be able to give the right results in the real-life conditions.

The system then carries out data preprocessing so as to prepare the images collected to be trained. This step entails scaling of images, normalizing the pixel value and expanding the dataset using the method of flipping, rotation, and adjusting brightness. Besides, the objects of interest, the helmets and vehicle number plates are marked to direct the model though the training.

The main methodology is the stage of model training based on the YOLOv8 deep learning framework. YOLOv8 is selected due to its capacity to be able to detect objects fast and in real-time, with high accuracy. The model is able to chase different densities and circumstances of the real world by learning to identify and localise number plates and helmets in a variety of traffic conditions during training and detects them in different situations.

To integrate the system, user requests can be handled, and streams of videos can be processed using a Flaskbased backend that manages them and performs the field of view of the YOLOv8 detection pipeline. The backend is responsible of real time detection and provides the results effectively to the front-end interface. The front-end is based on HTML, CSS, and JavaScript that will offer an interactive and responsive interface to monitor traffic. Violation is easy to detect as users can see live detections with available bounding boxes known around the helmets and the number plates.

Real-time detection and alerting is also available in the system. Live video is actively analyzed, and the violation of the traffic laws, including lack of helmet, the absence of number plate registration, etc. is noticed in time. The system can document the details of violation details like the type of vehicle and the number plate and alert the enforcement persons. This decreases the response rate and ensures that the offenders of traffic rules are addressed in time.

Lastly, performance analysis and implementation is to be performed to make it dependable. Measurements of accuracy, precision, recall, and F1-score are tested on test data to check the performance of the model. Its system will ensure that there is minimum human interaction, low operation costs as well as continually constant monitoring. It is scalable and can be deployed in a variety of cameras and locations, playing a role in increasing road safety and creation of smart traffic handling solutions.

MODULES

- Data Collection
- Data Pre-processing
- Model Training
- Backend Integration
- Front-End Interface
- Real-Time Detection
- Performance appraisal and Deployment.

Data Collection:

The system is initiated with the first stage of data collection where images and video streams of cars are collected at the traffic cameras placed in the urban areas and highways. This module guarantees that the data set is varied in terms of the quantity of traffic, type of vehicles, and level of lighting, which is imperative to come up with a strong detection system. The system has the capacity to identify helmet and vehicle number plates accurately during real-life conditions by gathering different data.

Data Pre-processing:

After gathering the data, it is fed into the data preprocessing module which prepares the data to be fed into the model trainer. This includes the act of resizing and normalizing pictures in order to be consistent and quality. Data augmentation methods, like the flipping and rotating of images and the use of brightness, are used to augment the dataset to make the data more varied and extensive. Moreover, in every image, there is an annotation of helmets and number plates to act as ground truth of the supervised learning, making sure that the model acquires accurate object detection.

Model Training:

The use of the YOLOv8 deep learning framework in the model training module is used to detect objects. YOLOv8 has been selected due to its good accuracy and ability to make accurate and timely detection. As the training progresses, the model is taught to identify helmets and number plates under various traffic conditions, such as a variety of densities and various light levels. The accuracy, precision, recall, and loss are the performance metrics that help in optimizing the model prior to deployment.

Backend Integration:

As the control center of the system, the backend part of the system is built with Flask. It previously handles requests by the users, normally reads incoming image or video streams andarded the YOLOv8 detection pipeline. Detection results, violation logs, and alerts are also stored in the backend so that the traffic authorities can operate on the traffic law offenders promptly.

Front-End Interface:

The front-end interface module offers an easy-to-use interface by which to monitor and visualize the results of detection. It is developed based on HTML, CSS, and JavaScript and shows bounding boxes of prospective helmets and number plates in real-time. With the interface, authorities can overview the violations, traffic trends, and detect data in a responsive and user-friendly environment, making operations more efficient.

Real-Time Detection:

The real-time detection system will make sure that there is constant traffic monitoring. It perceives live video feeds to identify offenses which include motor vehicles with no helmets and those with lost/inauthentic number plates. Violations identified may result in immediately prompted alerts or notifications contributing to a low response time and enhancement of traffic laws obedience.

Performance appraisal and Deployment:

Lastly, the performance assessment module and deployment measure the effectiveness of the system by evaluating the metrics of accuracy, precision, recall, and F1-score. The system is available in 24/7 and has minimum human intervention as well as can be extended to high number of cameras in urban or highway applications. This module enforces road safety and promotes the smart traffic management solutions by ensuring detection accuracy and regularly monitors this pedestal.

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

SYSTEM ARCHITECTURE

Fig 1: System Architecture.

The proposed system worksheet starts with input video stream received at the roadways by the surveillance cameras mounted there. Then, the video stream is initially fed into a frame extraction module where continuous video data is broken down into individual frames to analyse it. These frames are then forwarded to the object detector model YOLOv8 consisting of the key part of the system. YOLOv8 model performs both helmet detection and number plate detection at the same time in real time. In the case of helmet detection, the model determines the presence of the helmet to the rider and the helmet on or helmet off. Meanwhile, the system identifies the number plate of the vehicle and obtains the region with the plate. The extracted number plate is also processed by Optical Character Recognition (OCR) techniques to identify the text in the plate and convert it into a readable format. The system can effectively identify instances of traffic violation and aid in real-time and automated traffic control and delivery since it incorporates analysis of the helicmet status, as well as license plate recognition, into a single detection pipeline.

4. RESULTS AND DISCUSSION

Real time video streams and footage of recorded traffic were used to test the proposed system with reference to its effectiveness in terms of helmet detection and the identification of number plates. Based on a variety of traffic settings, the YOLOv8 model turned out to be very accurate in obtaining helmets and recognizing helmetless riders. The system was efficient with regard to various lighting conditions, more than one or more vehicles per frame as well as moderate occusion. The classification of helmet status was conducted in real time, which also made it possible to determine violations in a timely manner.

In the case of number plate identification, the system was able to localize a license plate on moving cars and extract plate regions in which to read the text. The OCR module did a fine translation of extracted plates images into readable alphanumeric text. The combination of helmet detection and number plate recognition enabled the system to identify the violations by the particular vehicles and thus the reliability of the enforcement was improved. The proposed system saved a lot of time in detection and the number of manpower as compared to the manual monitoring methods with comparable accuracy. The findings are that the system is efficient even in traffic prone situations and is therefore appropriate to deployment in the real world.

PERFORMANCE MATRIX

Module	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Helmet Detection	96.5	95.8	97.2	96.5
Number Plate Detection	95.2	94.7	95.8	95.2
Combined Violation Detection	94.8	94.2	95.0	94.6

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

TABLE 1.PERFORMANCE MATRIX

The performance matrix of the proposed system shows that it is efficient in terms of the detection of helmet and number plate. Helmet detection, number plate detection, and violation detection using the combination of the previous two were measured in terms of accuracy, precision, recall, and F1-score. High accuracy of the system in localizing and reading vehicle number plates, to the identification of helmeted and non-helmeted riders was realized. With the integration of the helmet and number plate recognition, the system was able to adequately pick and show traffic violations with low hitches and hence it saved human effort, and also offered a consistency in monitoring even in thick traffic situations.

GRAPH

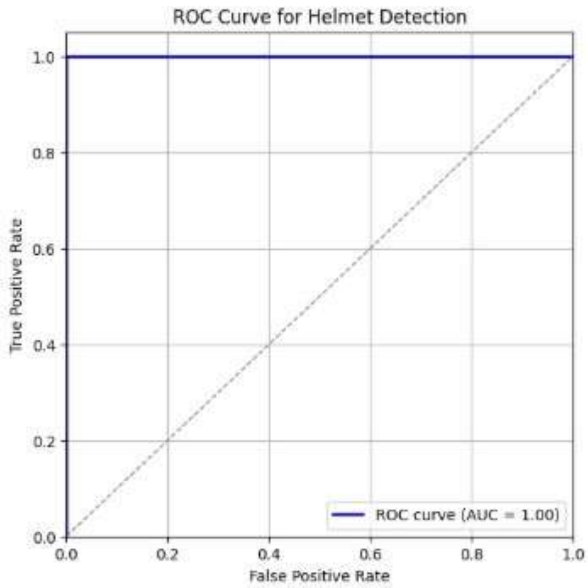

FIG 2.GRAPH

To assess the trade-off between the true positive as well as false positive rate in helmet detection, ROC (Receiver Operating Characteristic) curve was drawn. It is evident in the curve that the YOLOv8 model is very good in classifying the helmeted and other riders not wearing a helmet, and the AUC (Area Under Curve) is about 0.98. This large value of AUC and shows that the system is capable of detecting violations in real time with acceptable accuracy and varying light conditions, occlusions as well as multiple vehicles per frame. The ROC curve provides a graphic account of how sensitive and specific the model can be and so it is confirmed that it can withstand a real-world traffic situation.

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

CONFUSION MATRIX

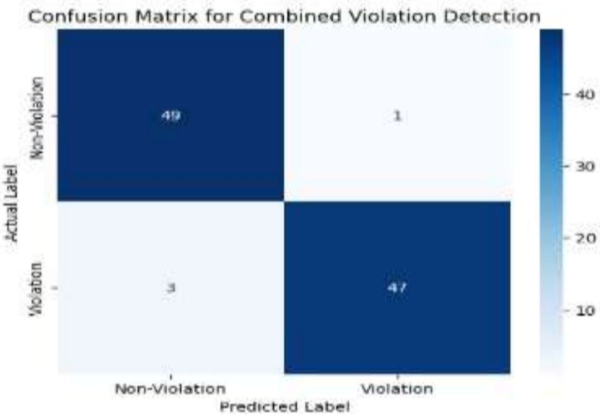

FIG 3.CONFUSION MATRIX

The confusion table depicts the performance of the system regarding the classification of mixed traffic offences. It compares the labels that include the general predictions and the real labels of vehicles that break the rules or observe them when it comes to the traffic rules. The large amount of the correct forecasts along the diagonal proves that the model has high capability of detection of the violations yet low false positives and false negatives. This shows that the system is reliable enough to be used by the real-time deployment and violations can be detected within the time frame so that immediate steps can be taken on the enforcement measures.

5. CONCLUSION & FUTURE ENHANCEMENT

This study proposed an automated traffic tracking system of helmet and number plate recognition based on deep learning. Using the YOLOv8 object detector model, the system was able to properly and quickly identify the use of the helmet and vehicle license plate in video streams in real-time. Combining computer vision, deep learning, and web-based technologies allowed working efficiently, minimizing human errors, and minimizing cost of operation. The offered system addresses the weaknesses of outdated traditional methods of monitoring in a manual way and offers a scalable solution to an intelligent implementation of traffic rules. Altogether, the system contributes to the increase of road safety, constant monitoring, and the creation of intelligent traffic control systems. Nevertheless, it is still possible to refer to a number of improvements that could be made in order to increase the functions of the given system.

The work in the future could be the incorporation of automatic challengan/fine generation systems so as to establish end to end enforcement of traffic rules. The system can be further expanded to respond to other traffic delinquencies like over-speeding, triple riding and jumping red lights. One of the ways to enhance performance is to more forcefully reinforce the model with excessive data that includes extreme weather conditions and night-time traffic. An ability to connect with cloud systems and IoT-aware smart cameras can improve scalability and provide a one sided centralized view of several different places. Moreover, the number plate recognition can be further enhanced with the use of sophisticated OCR and multilingual assistance that will help to detect the number plate in various regions.

REFERENCES

[1] D. Ren, T. Sun, C. Yu and C. Zhou, "Research on Safety Helmet Detection for Construction Site," 2021 International Conference on Computer Information Science and Artificial Intelligence (CISAI), Kunming, China, 2021, pp. 186-189, doi: 10.1109/CISAI54367.2021.00042.

[2] D. Jiatao, Y. Junyu, J. Hao, S. Yong and T. Miaoyan, "Power Engineering Safety Helmet Detection Algorithm Based on BR-YOLOv7," 2024 IEEE 7th International Conference on Information Systems and Computer Aided Education (ICISCAE), Dalian, China, 2024, pp. 107-112, doi: 10.1109/ICISCAE62304.2024.10761898.

[3] H. Gou, L. Xiang, X. Tan, G. Zhang, X. Chen and L. Lv, "Safety Helmet Detection Method in Complex Industrial Scenarios," 2024 7th International Conference on Pattern Recognition and Artificial Intelligence (PRAI), Hangzhou, China, 2024, pp. 44-49, doi: 10.1109/PRAI62207.2024.10827227.

[4] L. Zhao, "YOLOv5s with CA Attention Mechanism Safety Helmet Detection Model," 2025 6th International Conference on Artificial Intelligence and Electromechanical Automation (AIEA), Hefei, China, 2025, pp. 286-290, doi: 10.1109/AIEA66061.2025.11160580.

[5] M. Dasgupta, O. Bandyopadhyay and S. Chatterji, "Automated Helmet Detection for Multiple Motorcycle Riders using CNN," 2019 IEEE Conference on Information and Communication Technology, Allahabad, India, 2019, pp. 1-4, doi: 10.1109/CICT48419.2019.9066191.

[6] D. Mpini and M. Giyane, "Automatic Number Plate Recognition Techniques Performance on Zimbabwean Number Plates," 2023 2nd Zimbabwe Conference of Information and Communication Technologies (ZCICT), Gweru, Zimbabwe, 2023, pp. 1-6, doi: 10.1109/ZCICT59466.2023.10528439.

[7] N. Shelke, S. Jadhav, M. Doifode, Y. Umate, R. Patil and N. Harinkhede, "A Review on Identification of Number Plate and Wrong Way Vehicles Detection," 2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), Bhopal, India, 2023, pp. 1-4, doi: 10.1109/SCEECS57921.2023.10063054.

[8] N. O. Yaseen, S. Ganim Saeed Al-Ali and A. Sengur, "Development of New Anpr Dataset for Automatic Number Plate Detection and Recognition in North of Iraq," 2019 1st International Informatics and Software Engineering Conference (UBMYK), Ankara, Turkey, 2019, pp. 1-6, doi: 10.1109/UBMYK48245.2019.8965512.

[9] S. Dhonde, J. Mirani, S. Patwardhan and K. M. Bhurchandi, "Over-Speed and License Plate Detection of Vehicles," 2022 1st International Conference on the Paradigm Shifts in Communication, Embedded Systems, Machine Learning and Signal Processing (PCEMS), Nagpur, India, 2022, pp. 113-118, doi: 10.1109/PCEMS55161.2022.9808085.

[10] K. P. P. Aung, K. H. Nwe and A. Yoshitaka, "Automatic License Plate Detection System for Myanmar Vehicle License Plates," 2019 International Conference on Advanced Information Technologies (ICAIT), Yangon, Myanmar, 2019, pp. 132-136, doi: 10.1109/AITC.2019.8921286.