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Intelligent Traffic Monitoring: Detection of Helmetless Riders and Motorcycle License Plate Recognition using YOLOv8

Dimas Rossiawan Hendra Putra[a,1*], Hendro Darmono[a,2], Delila Cahya Permatasari[a,4], Adi Candra Kusuma[a,5]

[a] State Polytechnic of Malang, Jl. Soekarno Hatta No.9, Jatimulyo, Kec. Lowokwaru, Kota Malang, Jawa Timur 65141, Indonesia
[1] dimas.rossi@polinema.ac.idr*; 2hendrodarmono@polinema.ac.id; 3delila.cahya@polinema.ac.id; 4candraraden45@polinema.ac.id
[*] corresponding author

A B S T R A C T

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Traffic accidents involving motorcycle riders are often caused by a lack of education on road safety. One of the primary factors contributing to traffic accidents is rider negligence, which accounts for the largest percentage at 61%. Traffic accidents can result in severe injuries. One way to prevent severe injuries during an accident is by using safety riding equipment, such as helmets, while riding. Therefore, this study proposes a system for detecting helmet violations and recognizing license plates, which can facilitate the communication of information to the authorities. The detection system utilizes a CNN algorithm with the YOLO model to detect riders, helmets, no-helmets, and vehicle license plates. This research will implement a violation detection and license plate recognition system by deploying an IP Camera to record objects in real-time using dummy violation data. The system also employs Optical Character Recognition (OCR) to extract text from detected license plates, which will then be sent as notifications via the Telegram application. The YOLOv8 model training achieved an mAP score of 84.2%, with the accuracy for each class as follows: rider accuracy at 94%, no-helmet accuracy at 93%, license plate accuracy at 93%, and helmet accuracy at 87%. The license plate recognition system operates optimally at a distance of 1 to 5 meters, with an accuracy of 93.7% at 1 meter, 65% at 2 meters, 90% at 3 meters, 62.5% at 4 meters, and 51.7% at 5 meters.

1. Introduction

The Central Bureau of Statistics (BPS) released the Indonesia 2023 statistics report, which noted that there were 125,267.3 units of two-wheeled vehicles or motorcycles at the end of 2022 in Indonesia [1]. During the 10-years from 2012-2022 the number of two-wheeled vehicles continued to increase significantly with a percentage increase of 64% or an increase of 48.9 million units of two-wheeled vehicles and in East Java became the province with the largest number of two-wheeled vehicles in 2022, namely 20.7 million units of two-wheeled vehicles [2][3] explained that the number of traffic accidents increased by 34.6% compared to the previous year. Korlantas Polri also explained about several things that caused the occurrence of traffic accidents, including human negligence factors with the largest percentage of 61%, then infrastructure and environmental factors with 30%, and the smallest was caused by vehicle factors with 9%. One way to prevent serious injuries during an accident is to wear a helmet when riding, and reducing injuries experienced by riders during accidents can be minimised if the head is protected by a helmet [4].

Policies that regulate the use of helmets when riding have been widely socialised, which specifically discuss the use of helmets when riding motorcycles in terms of benefits, regulations, and fines, complete with the number [5]. As explained in article 106 paragraph (8) of Law No. 22/2009 which reads: "Every person who drives a motorcycle and motorcycle passengers must wear a helmet that meets Indonesian standards", If you violate this rule, you will be sentenced to sanctions which are regulated in article 291 paragraph (1) and (2) of Law No. 22/2009, paragraph (1) reads: "Every

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person who drives a motorcycle without wearing an Indonesian national standard helmet as referred to in Article 106 paragraph (8) shall be punished with a maximum imprisonment of 1 (one) month or a maximum fine of Rp250,000.00 (two hundred fifty thousand rupiah)", and paragraph (2) reads: "Every person driving a motorcycle who allows his passenger not to wear a helmet as referred to in Article 106 paragraph (8) shall be punished with imprisonment of not more than 1 (one) month or a maximum fine of Rp250,000.00 (two hundred fifty thousand rupiah)" [6].

Previous research developed a helmet detection system for motorcycle users using the Convolutional Neural Network (CNN) method. This system uses YOLOv3 as a helmet detector and takes input in the form of video [7]. Previous studies have demonstrated the effectiveness of object detection algorithms such as YOLO and TensorFlow Lite in vehicle classification and helmet violation detection, with inputs primarily from CCTV or real-time traffic cameras. While these works achieved high detection accuracy, they were often limited to recognizing a small number of object classes or lacked end-to-end integration with notification systems [8] - [10]. Additionally, OCR-based license plate recognition has been explored, but often with varying levels of accuracy at different distances [11]. This research will implement a helmetless rider violation detection system and vehicle license plate recognition by applying an IP Camera as a device to record objects in real-time using dummy violation data. This system uses the You Only Look Once Version 8 (YOLOv8) method, which is used to detect objects and uses the Optical Character Recognition (OCR) method as a text extractor from the detected license plate, which will be sent via the Telegram application as a notification.

2. Method

The dataset used in this study was constructed by extracting frames from recorded video footage, which were then converted into individual images for annotation. The additional data also came from online searches via Google. This study is conducted using a dataset categorised into four distinct classes: *rider*, *helmet*, *non-helmet*, and *license plate*. To ensure optimal performance during the training phase, only high-quality images were selected. High-resolution images enhance object recognition capabilities during the learning process. Each image in the dataset was manually annotated and labelled to distinctly identify and differentiate between the four aforementioned object classes. Following the labelling process, the dataset was partitioned into three subsets: training, validation, and testing. The training data is used to train the model, validation data evaluates model performance during training, and testing data assesses the generalisation capability of the final model. Specifically, 70% of the labelled images were allocated to the training set, 20% to the validation set, and the remaining 10% to the testing set. This distribution is designed to provide a balanced trade-off between learning efficiency and performance evaluation.

To enhance the diversity of the dataset and improve the robustness of the trained model, data augmentation techniques were applied post-labelling. The augmentation procedures implemented in this study include horizontal flipping, shear transformation, and brightness adjustment. These techniques introduce controlled variations in the dataset, thereby enabling the model to generalise better to real-world conditions. Once the augmentation process was completed, the expanded dataset was exported and subsequently utilised for training on the Google Colaboratory platform. This cloud-based environment facilitates scalable and efficient training by leveraging high-performance computational resources.

The training and evaluation processes were conducted utilising both the Roboflow web platform and the Google Colaboratory environment. Initially, a total of 500 original images were collected. Following data augmentation procedures, which included horizontal flipping, shear transformation, and brightness adjustment, the dataset was expanded to a total of 1000 images. Labelling was performed using the Roboflow platform, wherein each object instance within the images was annotated according to its corresponding class: *rider*, *helmet*, *non-helmet*, and *license plate*. This annotation process is critical to ensure accurate class identification during model training.

The examples of the annotated training images, illustrating each object class: helmet, non-helmet, motorcycle rider, and license plate, are presented in Fig.1.

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Fig. 1. Assigning each label to the image

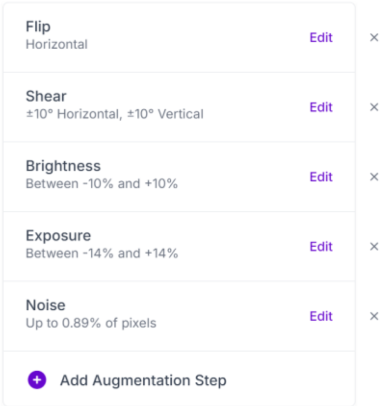

Fig. 2. Dataset augmentation

The proposed system comprises several integrated components designed to perform real-time object detection for motorcycle-related violations. An IP camera functions as the primary data acquisition unit, capturing live video or still images from the surveillance area. These visual inputs are transmitted to a Raspberry Pi, which serves as the core processing unit. The Raspberry Pi executes object detection algorithms to identify predefined classes such as helmet, non-helmet, rider, and license plate. All system scripts and models are stored on a memory card, which acts as the local storage medium for the Raspberry Pi. To enable remote alert delivery, the Raspberry Pi connects to the internet via an access point, allowing seamless communication with external platforms. Detected violations are then forwarded to the Telegram messaging platform through a bot using the Telegram API token. The end user receives real-time notifications, including relevant image evidence, via the Telegram application, thereby ensuring immediate and remote monitoring capabilities.

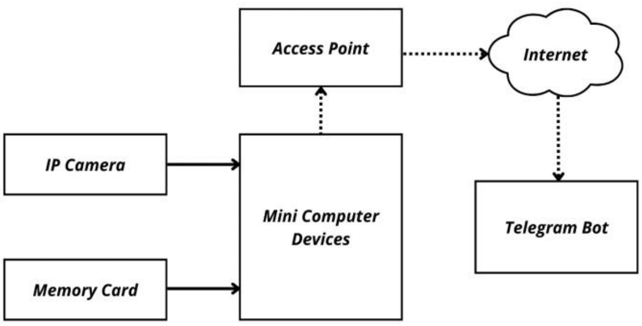

Fig. 3. Block diagram system

The system workflow, as depicted in the flowchart, begins with the initialisation of video capture from an IP camera, which continuously streams frames to be processed. These frames are then analysed to detect the presence of a motorcycle rider. If no rider is detected, the system resumes frame reading until a detection occurs. Once a rider is identified, the process transitions to the next stage, denoted as point (A). At this stage, the system performs helmet detection using a pre-trained object detection model. If the rider is wearing a helmet, the system considers it a non-violation case and returns to the initial monitoring phase. Conversely, if the rider is detected without a helmet, the system proceeds to recognise the vehicle's license plate using Optical Character Recognition (OCR), extracting the alphanumeric data from the image. After successful extraction, the system compiles the evidence, consisting of the rider's photograph and the corresponding license plate information, and transmits it to the end user via the Telegram messaging platform using a Telegram Bot API. This stage is indicated as point (B). The user receives the violation alert in real time through the Telegram application, thereby completing the process as shown in the final steps of the flowchart.

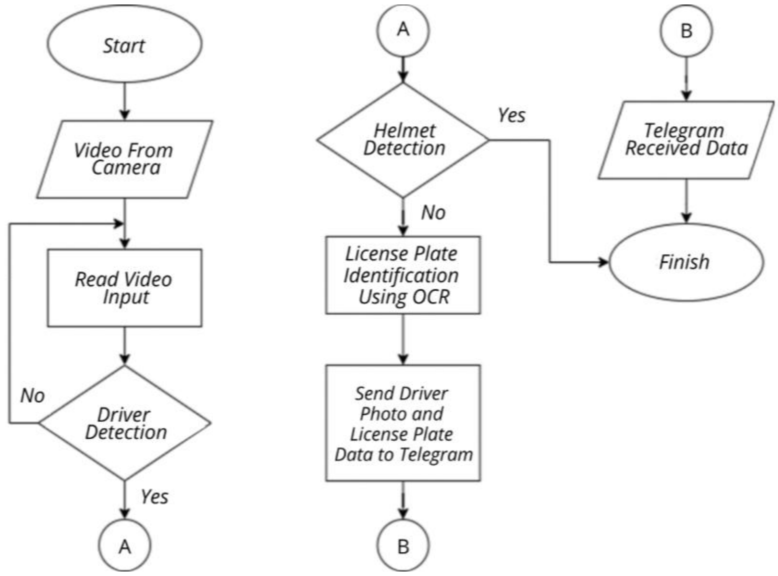

Fig. 4. Flowchart of the helmet violation detection system and vehicle number plate extraction

During the software design phase, a Telegram-based chatbot system was implemented to automate the delivery of violation reports, including detected object images. The development process began with installing the Telegram application via the Google Play Store, followed by account registration using a valid phone number.

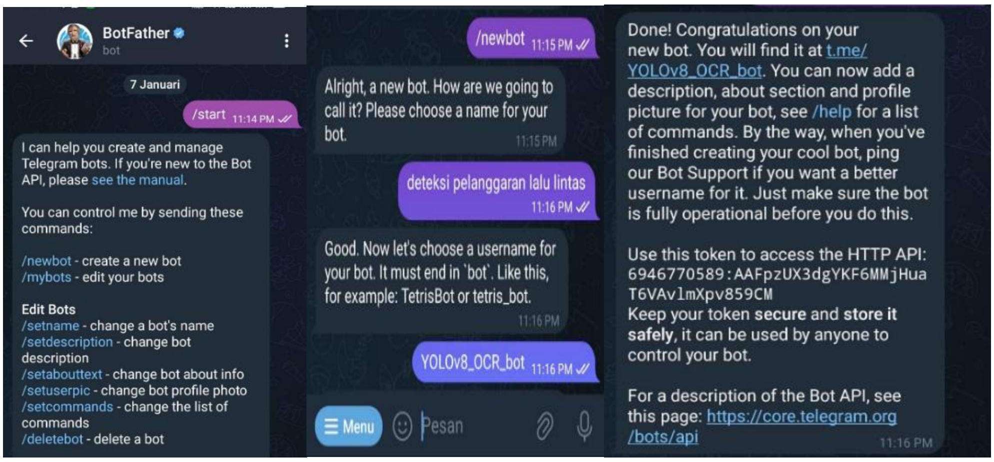

Fig. 5. Telegram-based chatbot

Users then accessed "BotFather", Telegram's official bot management tool, through the app's search function. By issuing the /start and /newbot commands, a new chatbot was created, complete with a designated name and unique username. Upon successful creation, BotFather generated a unique authentication token, which is essential for accessing the Telegram Bot API. This token's later used during system integration to enable the chatbot to receive and transmit violation information and detection images automatically. The implementation of this Telegram chatbot enhances system responsiveness and facilitates efficient real-time communication in the context of violation monitoring.

3. Results and Discussion

The results of the hardware design use an IP camera mounted on a tripod that can be adjusted in height. The Raspberry Pi and ip camera are connected to the same network so that they can communicate with each other. A cellphone that has the Telegram application installed is used to receive notifications if a rider who does not wear a helmet is detected.

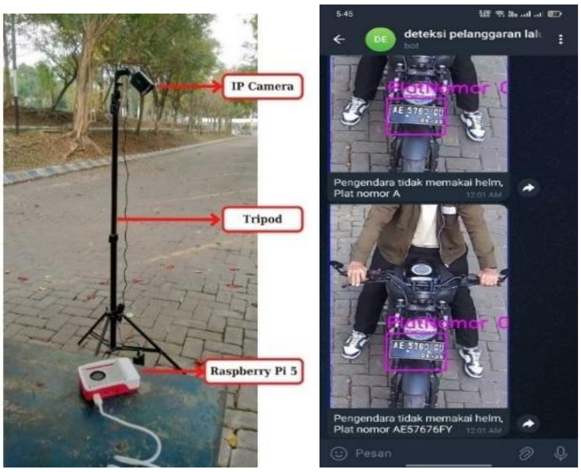

Fig. 6. Hardware and software implementation

The results of the software design demonstrate the successful implementation of a Telegram-based communication system utilising BotFather to create and manage a custom chatbot. This chatbot is specifically developed to receive and transmit real-time violation data detected by the system. The software design integrates the Telegram Bot API with an object detection module, allowing seamless communication between the detection unit and the end user via the Telegram platform. Upon detecting a violation, such as not wearing a helmet, the system captures an image of the violation proof and extracts relevant data, including the vehicle's license plate number. This information is then formatted into a structured message consisting of both textual data and visual evidence. The Telegram chatbot, registered and configured through BotFather, is programmed to receive these messages automatically. The bot operates in real time, ensuring that every violation event is promptly relayed to the designated Telegram chat. This enables system operators or relevant authorities to monitor violations remotely without needing to manually retrieve data from local storage or surveillance systems. The software design also includes authentication mechanisms to ensure secure access to the bot, preventing unauthorised users from retrieving sensitive information.

The training process was conducted over 200 epochs using the augmented dataset, with careful tuning of hyperparameters to optimise model performance. As a result, the model achieved a mean average precision (mAP) score of 0.842. This value indicates a high level of accuracy in detecting and localising objects associated with helmet violations. The training process was conducted on Google Colaboratory with a configuration of 200 epochs and a batch size of 24. The training performance was monitored using a series of loss and evaluation metric graphs, which provide insights into how well the model learned from the data and how effectively it generalised during validation. The graph labelled train/box_loss shows the decline in bounding box regression loss throughout the training process. This decreasing trend indicates that the model progressively improved in adjusting bounding boxes to more accurately match the ground truth positions of objects in the images. Similarly, the train/cls_loss graph reflects the reduction in classification loss over time, suggesting that the model became increasingly effective at distinguishing between object classes. In addition, the train/dfl_loss graph (Distribution Focal Loss) demonstrates a steady decline, indicating that the model improved its focus on object regions deemed most important during training. This is crucial for achieving better localisation and attention across diverse object shapes and sizes. Validation loss graphs, val/box_loss, val/cls_loss, and val/dfl_loss, follow similar downward trends, which confirms that the model not only learned effectively from the training data but also generalised well on unseen data. These results suggest minimal overfitting and good stability during the learning process.

Performance metrics were also tracked. The metrics/precision(B) graph shows an increasing trend in precision, implying that the model made fewer false positive detections as training progressed.

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Meanwhile, metrics/recall(B) indicates improved recall, meaning the model was able to detect a higher proportion of true objects present in the dataset. The metrics/mAP50(B) graph illustrates the increase in mean Average Precision (mAP) at an IoU threshold of 50%. This metric is commonly used to assess the overall accuracy of object detection models, and its improvement signifies better object recognition and classification. Lastly, the metrics/mAP50-95(B) graph—representing mAP across multiple IoU thresholds from 50% to 95%—also shows positive progression, indicating that the model maintained strong detection performance even under more stringent localisation criteria. Overall, the training graphs confirm that the model improved steadily in both localisation and classification tasks, and the results point to a well-generalised model capable of performing object detection reliably across varied scenarios.

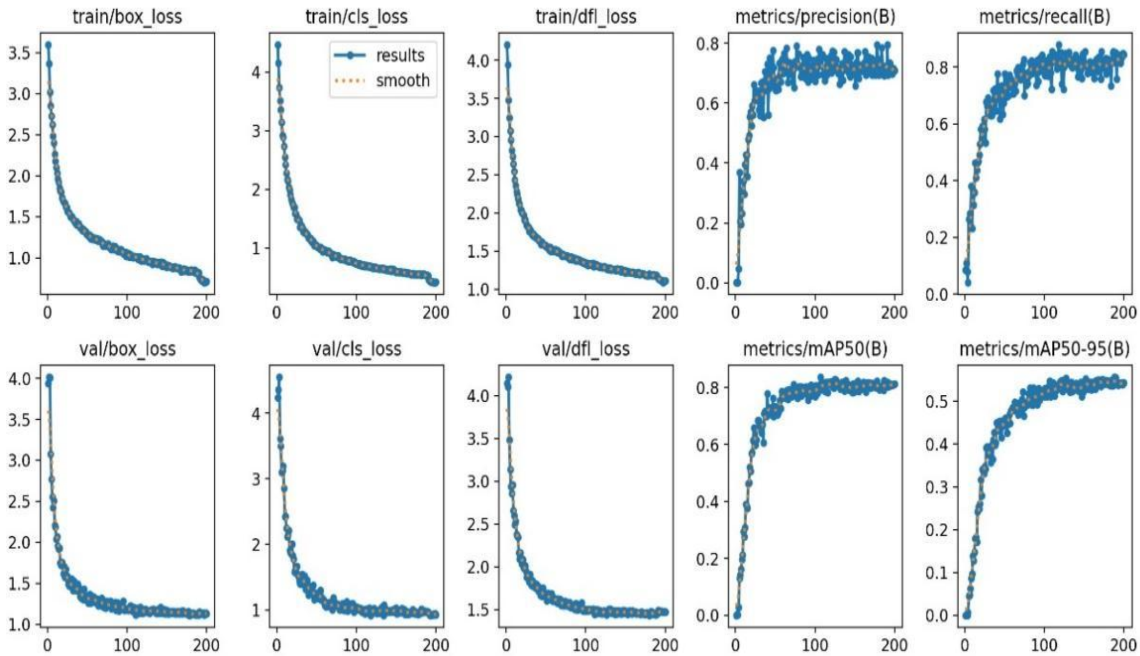

Fig. 7. Training results

The confusion matrix provides a detailed overview of the model's classification performance across each object class. In this study, the object detection model was trained to identify four target classes: helmet, no helmet, rider, and license plate, with an additional class labelled background representing non-object areas. The diagonal values of the confusion matrix indicate the number of correct predictions for each class, while off-diagonal values reflect instances of misclassification. Based on the results, the helmet class was correctly predicted in 72% of cases, whereas the no-helmet class achieved a higher correct prediction rate of 91%. The rider class showed strong performance with 96% accuracy, and the license plate class followed closely with 94% accuracy. These values demonstrate that the model performs reliably for key object categories involved in the violation detection task.

However, misclassifications were still present. For instance, 3% of helmet objects were incorrectly classified as no-helmet, and conversely, 6% of no-helmet objects were misclassified as helmets. These errors, though relatively small, suggest that visual similarities or partial occlusion might contribute to confusion between these two classes. The background class exhibited a higher rate of misclassification. Specifically, 29% of background regions were incorrectly predicted as helmets, 16% as no helmet, 6% as rider, and 13% as license plates. This indicates that the model occasionally misinterprets non-object areas as meaningful objects, which could be due to noise in the image, complex backgrounds, or insufficient representation of background samples during training. Overall, while the model demonstrates strong classification performance across most object classes, the confusion matrix highlights key areas particularly in background differentiation where further improvements in dataset quality or model tuning may enhance accuracy and reduce false positives.

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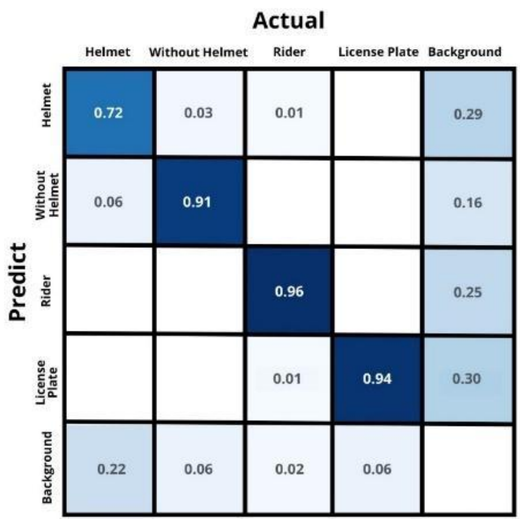

Fig. 8. Confusion matrix

Table 1 presents the overall performance metrics for each object class evaluated in the study. Among the four target classes, helmet, no helmet, rider, and license plate. The helmet class consistently demonstrates lower performance compared to the others. This discrepancy may be attributed to the quality and clarity of the images associated with the helmet class used during training. In several instances, helmets were partially occluded, blurred, or captured under suboptimal lighting conditions, making it more challenging for the model to accurately learn and recognise helmet features. In contrast, the rider, license plate, and no-helmet classes exhibited higher and more stable performance across various metrics, likely due to better image representation and more distinct visual characteristics. These results suggest that future improvements in training data quality, particularly for the helmet class, could contribute significantly to enhancing the model's detection accuracy and overall robustness

Table 1. Performance table for each class

Class	Performance			
	Accuracy	*Precision*	*Recall*	*F1-Score*
Helmet	87%	72%	68%	70%
Without Helmet	93%	91%	80%	85%
Rider	94%	96%	79%	86%
Plat License	93%	94%	75%	83%

Object detection testing under static speed conditions was conducted to evaluate the impact of object distance on detection accuracy using the trained YOLOv8 model. By systematically adjusting the distance between the object and the detection system, the experiment assessed how well the model could maintain its recognition performance as visual features became smaller or less distinct. This evaluation is critical for understanding the model's operational limits, particularly in scenarios such as surveillance or checkpoint monitoring, where object proximity can significantly influence detection accuracy. The results from this test serve as a benchmark for optimising camera placement and system sensitivity in practical deployments.

In one of the static object detection tests (5 Meters), the actual scene consisted of three distinct objects: one rider, one no-helmet instance, and one license plate with the identifier AE5763GU. The detection results produced by the trained YOLOv8 model accurately matched the ground truth. Specifically, the model successfully identified one rider, one no-helmet object, and correctly detected the license plate, including its alphanumeric content AE5763GU. This outcome indicates a high level of accuracy under controlled conditions, suggesting that the model performs reliably in recognising key features when objects are stationary and clearly visible. The consistency between actual and predicted objects also demonstrates the model's capability in preserving character-level precision for license plate recognition, which is critical in traffic law enforcement applications.

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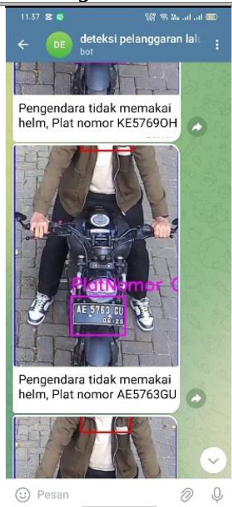
Table 2. Motionless object detection

Distance	Performance		
	Frame	***Telegram Result***	***Description***
1 Meter			**Actual Objects:** 1 rider, 1 without a helmet, 1 license plate (AE5763GU) **Predicted objects:** 1 rider, 1 without a helmet, 1 license plate (AE5763GU)
5 Meter			**Actual objects:** 1 rider, 1 without a helmet, 1 license plate (AE5763GU) **Predicted objects:** 1 rider, 1 without a helmet, 1 license plate (AEST53OY)
10 Meter		The photo was not sent to the Telegram bot because the license plate was not detected.	**Actual objects:** 1 rider, 1 without a helmet, 1 license plate **Predicted objects:** 1 rider, 1 without a helmet

On the other hand of the static object detection tests (10 Meters), the actual scene contained three primary objects: one rider, one without a helmet, and one license plate with the identifier AE5763GU. The YOLOv8-based detection model successfully identified the presence of all three objects, correctly detecting one rider and one no-helmet instance. However, while the model did detect a license plate, the alphanumeric output showed a recognition error. The detected plate was read as AEST53OY, which differs from the actual AE5763GU. This mismatch indicates a character-level recognition error in the license plate detection component, possibly caused by factors such as image blur, low contrast, font variations, or angle distortion. Such errors highlight the importance of improving optical character recognition (OCR) robustness within the system, particularly under real-world conditions where environmental variables can degrade detection accuracy.

At distances between 25 and 30 meters, the model was only able to reliably detect objects classified as riders, while failing to recognise other classes such as helmets, no-helmet, and license plates. This limitation is primarily attributed to the insufficient representation of long-range samples in the training dataset. As a result, the model struggles to distinguish between the actual objects and

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the background when the objects appear small or visually ambiguous at greater distances. This outcome highlights the importance of diverse and well-balanced training data, especially when the deployment environment involves varying object scales and distances. Enhancing the dataset with more examples of distant objects could improve the model's ability to generalise and maintain detection accuracy across a wider range of conditions.

4. Conclusion

This study has explored the application of deep learning techniques, specifically the YOLOv8 object detection model and Tesseract OCR, for addressing a real-world societal challenge: identifying traffic violations involving motorcycle riders not wearing helmets and recognising their license plates. Beyond the technical results, this research demonstrates how artificial intelligence can be thoughtfully integrated into public safety systems to support enforcement in a non-intrusive yet effective manner. The findings affirm the potential of convolutional neural networks to serve not only as a computational tool but as a bridge between technology and human-centred problem solving. While the model performed well under certain conditions, its limitations, particularly at longer distances, which is 5 meters above, highlight the importance of data diversity, contextual understanding, and continuous refinement.

Ultimately, this work is not just a step forward in traffic violation detection, but a reflection of how machine learning can be tailored to serve the public good when developed with intention, tested rigorously, and deployed responsibly. Future studies are encouraged to build upon this foundation, with a focus on scalability, edge-device implementation, and improved resilience across dynamic environmental conditions.

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References

[1] Badan Pusat Statistik, "Statistik Indonesia 2023". accessed on January 14, 2024 from: https://www.bps.go.id/id/publication/2023/ 02/28/18018f9896f09f03580a614b/statistik-indonesia-2023.html.

[2] Ahdiat, Adi. "Ini Pertumbuhan Jumlah Motor di Indonesia 10 Tahun Terakhir". accessed on January 14, 2024 from : https:// databoks.katadata.co.id/datapublish/2023/03/ 16/ini-pertumbuhan-jumlah-motor-di-indonesia-10-tahun-terakhir.

[3] Biro Komunikasi dan Informasi Publik, "Tekan Angka Kecelakaan Lalu Lintas, Kemenhub Ajak Masyarakat Beralih ke Transportasi Umum dan Utamakan Keselamatan Berkendara" accessed on January 14, 2024 from: https://dephub.go.id/post/read/%E2%80%8B tekan-angka-kecelakaan-lalu-lintas,-kemenhub-ajak-masyarakat-beralih-ke-transportasi-umum-dan-utamakan-keselamatan-berkendara.

[4] Muhammad, Daafa Alhaqqy. Maulana, Aditya. "Fenomena Rider Motor Tidak Pakai Helmet Kian Marak, Banyak yang Cuek," accessed on January 14, 2024 from: https://otomotif.kompas.com/read/2023/12/06/ 125209915/ fenomena-rider-motor-tidak-pakai- helmet-kian-marak-banyak-yang-cuek?page=all.

[5] Muhammad, Daafa Alhaqqy. Maulana, Aditya. "Fenomena Rider Motor Tidak Pakai Helmet Kian Marak, Banyak yang Cuek," accessed on January 14, 2024 from: https://otomotif.kompas.com/read/2023/12/06/ 125209915/ fenomena-rider-motor-tidak-pakai- helmet-kian-marak-banyak-yang-cuek?page=all.

[6] Febryanti, Kartika. "Undang-undang yang mewajibkan penggunaan helmet standar," accessed on January 14, 2024 from: https://www.hukumonline.com/klinik/a/ undang--undang-yang-mengatur-penggunaan-helmet-standar-kendaraan-roda-dua-cl4957.

[7] Albert. Gunandi, Kartika. Setyati, Endang. "Deteksi Helmet Pada Pengguna Sepeda Motor Dengan Metode *Convolutional Neural Network*" Jurnal Infra, vol. 8, no. 1, hal. 295-301, 2020.

[8] Aldhiyatika, Amwin. "Deteksi Dan Klasifikasi Kendaraan Berbasis Algoritma You Only Look Once (YOLO)" DuraSPace UII, hal.1-44, Agustus 2021.

[9] Jaya, I Gusti Alit Wiraguna. Swardika, I Ketut. Sugirianta, Ida BAgus Ketut "Sistem Deteksi Pelanggaran Pengendara Motor Dengan Computer Vision Sesi Pelanggaran Pelindung Kepala" Repositori Politeknik Negeri Bali, hal. 1-8, September 2022.

[10] Lou, H., Duan, X., Guo, J., Liu, H., Gu, J., Bi, L., & Chen, H. (2023). DC-YOLOv8: Small-Size Object Detection Algorithm Based on Camera Sensor. Electronics (Switzerland), 12(10). https://doi.org/10.3390/electronics12102323.

[11] Hanif, Ahmad Rizalul Hanif. Nasrullah, Emir. Setyawan, Arinto "Deteksi Karakter Plat Nomor Kendaraan Dengan Menggunakan Metode Optical Character Recognition (OCR)," JITET Jurnal Informatika dan Teknik Elektro, vol. 11, no. 1, hal. 109-117, 2023.