Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 15s (2025)
https://www.jneonatalsurg.com

AI-Enhanced Real-Time Cranio-Traumatic Injury Prevention Using CNN-Based Helmet Adherence Monitoring and YOLOv3-Assisted Vehicular Identification for Prognostic Accuracy in Neurotrauma Mitigation

Dr. M. Kathiravan*[1], Dr. M. Manikandan[2], Dr Arumugam S S[3], Dr Terrance Frederick Fernandez[4], Dr. A. Mohan[5], Dr. M Vijayakumar[6]

[1]Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS), Saveetha University, Thandalam, Chennai-602105. Email ID: kathiravanm.sse@saveetha.com
[2]Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS), Saveetha University, Thandalam, Chennai-602105. Email ID: manikandanm10@gmail.com
[3]Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS), Saveetha University, Thandalam, Chennai-602105. Email ID: ssarumugam.me@gmail.com
[4]Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS), Saveetha University, Thandalam, Chennai-602105. Email ID: frederick@ptuniv.edu.in
[5]Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS), Saveetha University, Thandalam, Chennai-602105. Email ID: annamalaimohan@gmail.com
[6]Department of Computing Technologies, School of Computing, SRM Institute of Science and Technology, Kattankulathur, Chennai – 603203. Email ID: vijayakm10@srmist.edu.in

***Corresponding Author:**
Dr. M. Kathiravan
Email ID: kathiravanm.sse@saveetha.com

Cite this paper as: Dr. M. Kathiravan, Dr. M. Manikandan, Dr Arumugam S S, Dr Terrance Frederick Fernandez, Dr. A. Mohan, Dr. M Vijayakuma, (2025) AI-Enhanced Real-Time Cranio-Traumatic Injury Prevention Using CNN-Based Helmet Adherence Monitoring and YOLOv3-Assisted Vehicular Identification for Prognostic Accuracy in Neurotrauma Mitigation. *Journal of Neonatal Surgery*, 14 (15s), 939-946.

ABSTRACT

Background: In 2023, over 50% of road fatalities in India were linked to motorcycle riders not wearing helmets. The inadequacy of current road safety systems in detecting such violations in real-time necessitates the development of more advanced, automated solutions.

Objectives: This study aims to develop a real-time system that accurately detects helmet usage and recognizes motorcycle license plates using state-of-the-art machine learning techniques, thereby reducing road fatalities and improving traffic law enforcement.

Materials and Methods: The system integrates Convolutional Neural Networks (CNN) for helmet detection and the YOLOv3 (You Only Look Once, version 3) model for motorcycle and license plate recognition. The input video is resized and pre-processed before being passed to the YOLOv3 model, which identifies and localizes motorcycles and license plates using bounding boxes and confidence scores. Non-maximum suppression is applied to refine the detections. For each motorcycle detected, a region of interest (ROI) is cropped and analysed by the CNN model to determine helmet usage, with classification output as "helmet" or "no helmet." The annotated video is stored for further evaluation.

Results: The system effectively detects and labels motorcycles and helmet compliance in real-time. Using video inputs with a resolution of 888 × 500 pixels, the model achieved a mean average precision (mAP) of 54.64%. The integration of CNN and YOLOv3 enhanced detection accuracy and system responsiveness.

Conclusion: The proposed system demonstrates the potential of deep learning-based approaches to significantly improve road safety by enabling real-time helmet detection and license plate recognition. This integrated solution can aid authorities in enforcing helmet laws and reducing motorcycle-related fatalities.

Keywords: *Helmet Detection, YOLOv3, Convolutional Neural Network, License Plate Recognition, Road Safety*

1. INTRODUCTION

The planet earth is surrounded by many beautiful, fascinating and useful natural resources, but in the past few decades we observed that our earth has faced many environmental issues like depleting of natural resources and further threatening to the valuable ecosystems. Different scientists of the world, policy makers, social activists, the political people and economists are very much concerned about the preservation and conservation of natural resources. The deep concern has showed by different research persons, environmentalists and engineers [2].

- Implement a real-time system for identifying non-helmeted motorcycle riders.
- Utilize the YOLOv3 Model and Custom CNN Model for efficient object detection and classification.
- Automate license plate detection to reduce the workload on traffic police officers.

Our research seeks to address the hypothesis that implementing an automated system for detecting non-helmeted motorcycle riders will contribute to improved road safety and increased helmet compliance. This research is essential as it aims to enhance road safety, reduce accidents, and protect the lives of motorcyclists. By automating the detection of non-helmeted riders, this system will not only reduce human resources but also encourage higher compliance with helmet-wearing regulations. The anticipated contribution of this project is the development of a real-time, automated system that can efficiently detect non-helmeted motorcycle riders. This innovation has the potential to significantly impact road safety and traffic management. The remainder of this article will delve into the methodology, experiments, and results of our research. We will explore how the YOLOv3 Model and Custom CNN Model are employed in creating the real-time detection system and present the findings from our experiments. Finally, we will discuss the implications and significance of our research in the context of road safety and public well-being.

2. RELATED WORK

2.1 LICENSE PLATE DETECTION

Detecting license plates for vehicles has posed a challenging but solvable puzzle for a multitude of researchers in recent years. Among the pivotal steps in the realm of Automatic Number Plate Recognition (ANPR), license plate detection stands out as a cornerstone [2]. The accuracy achieved during the license plate detection stage profoundly influences the precision of subsequent phases involving segmentation and recognition. Past research, such as [3] and [4], successfully harnessed the vertical Sobel operator to pinpoint vertical edges, subsequently facilitating plate verification by assessing the aspect ratio defined by width and height. However, it is worth noting that the presence of undesired edges can potentially introduce substantial complications, particularly for methods reliant on boundary analysis, as discussed in [5].

2.2 HELMET PREDICTION

In a similar vein, fellow researchers have put forth an approach that involves a two-step process: initially, the identification of motorcycle riders, followed by the assessment of their helmet usage. Chiverton [6] proposed the use of circular arc to identify helmet in a video feed, it has very low accuracy. On the other hand, given the number of vehicles on the speed at a given instant, the computation that required is very heavy and consumes lots of resources. This method will determine any circular object around the bike rider as helmet. In the work presented in [7], the authors proposed a method based on background subtraction for detecting moving objects, wherein the object is isolated and characterized through the extraction of features using Local Binary Pattern (LBP) [8]. Subsequently, once the motorcycle's position is determined, a top portion equivalent to 1/5 of the image is cropped to reveal the specific helmet region, which is further classified using a combination of LBP, Hough Transform, and Histogram of Oriented Gradients (HOG) descriptors. In parallel studies conducted by [9] and [10], there is a concurrent recommendation to employ connected component labelling after background subtraction to segment the object, a technique intended for object identification.

3. PROPOSED METHOLOGY

For the execution of this research, a comprehensive set of materials and methods was meticulously employed, catering to a systematic and thorough investigation. These encompassed equipment, software, and unique resources:

The primary tools employed in this study included a high-resolution digital camera for video capture, and a computer system with GPU (Graphics Processing Unit) support to facilitate real-time video analysis. The software arsenal comprised OpenCV, TensorFlow/Keras, and custom Python scripts. OpenCV served as the cornerstone for image processing and computer vision tasks, while TensorFlow and Keras provided the platform for developing machine learning models. Custom Python scripts were meticulously crafted to integrate and orchestrate the various components of the system.

To train and validate the machine learning models, diverse datasets were amassed, containing images and videos of motorcycle riders. These datasets were carefully curated to encompass a wide spectrum of scenarios, including instances with and without helmets. The sample employed for this research was an extensive collection of video footage, sourced from a multitude of diverse origins. It encompassed publicly available videos and proprietary video recordings, thereby representing a heterogeneous and ecumenical cross-section of real-world scenarios [11]. The sample featured motorcycle riders of varying age groups, gender, and demographic backgrounds, riding under a plethora of environmental conditions. The research conducted in this study did not directly engage with human participants. All data used in the research were publicly available videos or recordings from traffic surveillance cameras. Consequently, the need for specific consent from individuals or measures to protect privacy was deemed unnecessary [12]. Our research was meticulously orchestrated to follow a systematic and chronological sequence of events. The research process unfolded as follows:

Data Collection: An extensive array of video data was collated from an assortment of sources, encompassing both public video repositories and proprietary traffic surveillance footage.

Data Pre-processing: The acquired video data underwent an array of preprocessing steps. These encompassed resizing, frame extraction, and the conversion of the data into a format optimally suited for subsequent analysis.

Object Detection: The YOLOv3 Model was harnessed for the task of object detection, with a particular focus on identifying motorcycles and other relevant objects within the video footage.

Region of Interest (ROI) Extraction: To facilitate helmet detection, a predefined region of interest (ROI) was cropped from the top portion of the motorcycle rider's image.

Helmet Detection: A Custom CNN Model was deployed to undertake the task of helmet detection within the delineated ROI. This model effectively classified whether a helmet was present or absent.

License Plate Detection: As an integral component of the comprehensive system, the study encompassed license plate detection. This task was effectively executed using both the YOLOv3 and Custom CNN Models.

Data Analysis: The process of data analysis involved the systematic extraction of pertinent features. This process was paramount in producing insights and information for each frame of the video data.

Data Aggregation: The data obtained, including the results of helmet detection and license plate recognition, were judiciously aggregated and organized to facilitate the subsequent phases of analysis.

Statistical Analysis: The performance evaluation of the system was conducted through the systematic application of statistical analysis techniques. This stage involved the calculation of key metrics, including but not limited to accuracy, precision, recall, and F1-score.

Results Interpretation: The results obtained from the comprehensive analysis were judiciously interpreted. This process was instrumental in ascertaining the efficacy of the system, particularly in terms of helmet detection and license plate recognition.

To safeguard against potential bias, the research meticulously incorporated an array of controls. The datasets were sourced and curated with diversity in mind, including various video scenarios and environmental conditions. This approach facilitated a balanced and representative dataset, effectively minimizing any potential biases. Data analysis predominantly relied on statistical methods. These encompassed accuracy calculations, precision-recall analysis, and the systematic assessment of the system's performance in terms of helmet detection and license plate recognition [13]. The selection of these methods was underpinned by the need for quantitative and objective assessment. Statistical techniques are particularly well-suited for evaluating the accuracy and performance of the system in the context of helmet detection and license plate recognition. To bolster the reliability and validity of the analysis, rigorous cross-validation techniques were implemented. Baseline models were established to serve as a benchmark, facilitating a comparative analysis of the results. This approach reinforced the robustness and generalizability of the findings to real-world applications. A visual representation of the general system architecture is depicted in Figure 1, elucidating the data flow and the sequential steps involved in the real-time helmet and license plate detection system.

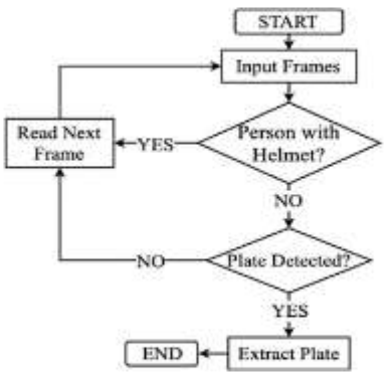

Fig. 1. General Structure of Proposed System

4. IMPLEMENTATION

In the implementation of our research, we utilized a well-defined hardware and software framework. The hardware setup included a high-performance computing system integrated with a powerful GPU, essential for managing the computational demands of real-time video processing. On the software side, the development environment incorporated several key tools and libraries: OpenCV was employed for image and video processing, TensorFlow and Keras were used for designing and training the machine learning models, and custom Python scripts facilitated the integration and coordination of the overall system components.

4.1 YOLO ALGORITHM

To perform object classification, we employed the YOLOv3 algorithm, which features a deep architecture consisting of 53 convolutional layers, five max-pooling layers, and soft-max activation functions (14). The input image is divided into an S × S grid, where each grid cell is responsible for predicting the presence of an object whose center falls within its boundaries. For each relevant cell, the model estimates four bounding box (BB) coordinates—namely, the width (w), height (h), and the center coordinates (cx, cy). Here, (cx, cy) represents the object's center location relative to the grid cell, while (w, h) correspond to its size in proportion to the overall image dimensions. A confidence score (c) is also generated, indicating the likelihood of an object being present in the specified grid cell. As illustrated in Figure 2, the yellow-highlighted grid cell demonstrates the prediction of the license plate, with the coordinates (cx, cy) pinpointing the grid cell that contains the center of the detected license plate.

bx = $\frac{(bx-cx)}{cx}$,

by = $\frac{(by-cy)}{cy}$,

$bw = \frac{bw}{W}$,

$bh = \frac{bh}{H}$, where W and H are the image dimensions

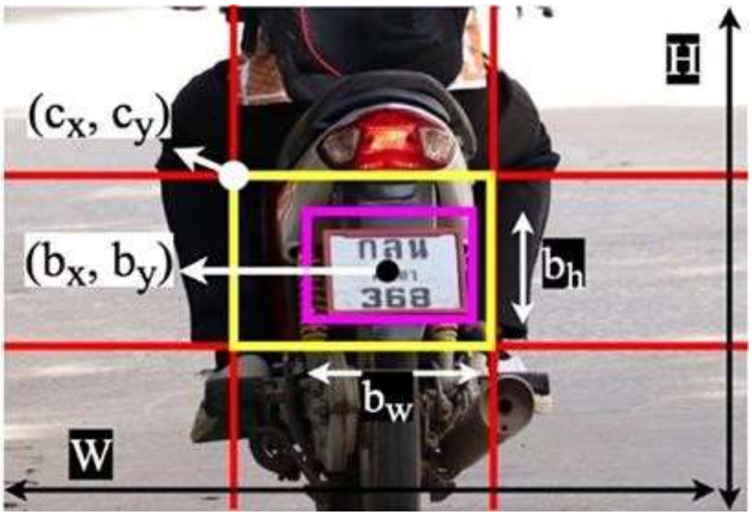

Fig. 2. Using 3 × 3 grid cells for illustration of YOLO.

As shown in Figure 2, the bounding box dimensions—width (bw), height (bh), and coordinates (cx, cy)—represent the object's position within the grid. The input data consisted of video footage from both public sources and proprietary recordings, capturing motorcycle riders in varied real-world scenarios. The implementation involved setting up the hardware and software environment, enabling GPU optimization, and fine-tuning parameters for both the YOLOv3 and custom CNN models.

Fig. 3. Motorcyclist wearing Helmet

As shown in figure 3, our algorithm accurately detects helmeted motorcyclists, marking them with a green bounding box. We evaluated the model on images containing both helmeted and non-helmeted riders to test its robustness. Figure 3 showcases result across various scenarios, including crowded scenes and solo riders. The system reliably distinguishes helmets from similar-looking objects like caps and scarves, demonstrating its precision and adaptability.

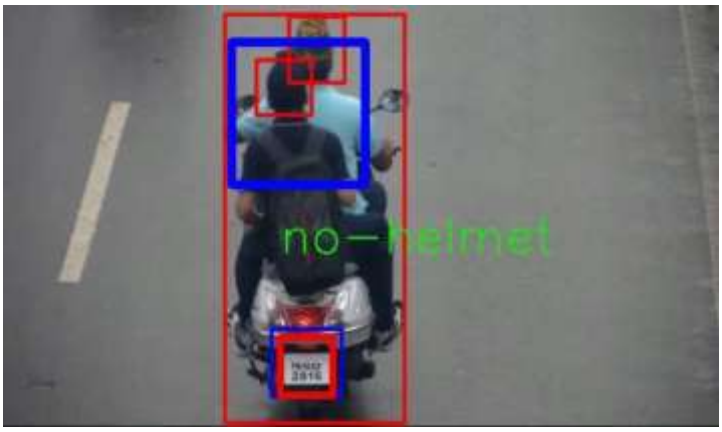

Fig. 4. License Plate detected for a Non - Helmeted Motorcyclist.

As illustrated in Figure 4, our algorithm successfully identifies motorcyclists without helmets by switching the bounding box color from green to red. Unlike the method proposed by A., which struggles to detect black helmets that blend with hair, our approach overcomes this limitation, accurately detecting helmets of all colors and shapes. As seen in Figure 2, the system also extracts license plates from non-helmeted riders, demonstrating its robustness and reliability across various conditions.

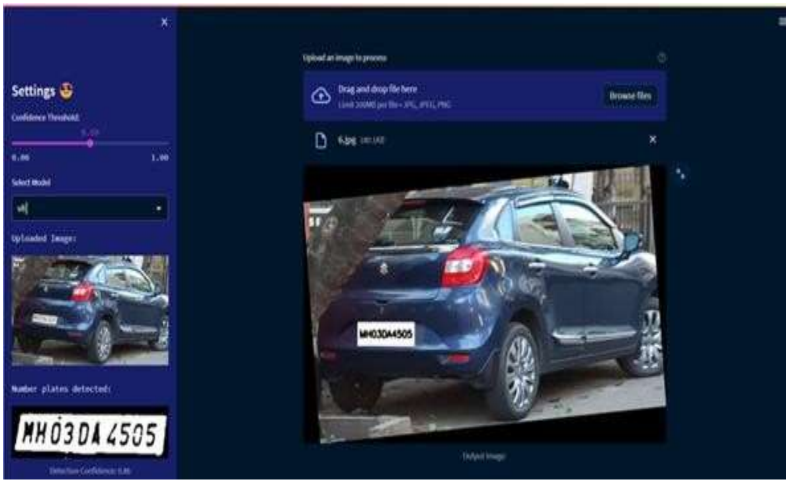

Fig. 5. Automatic License Plate Detection

Figure 5 illustrates the use of Streamlet to run our system via a web interface. Users can upload an image and select either the YOLOv5 or YOLOv8 model for detection. The graph shows the average training error across iterations. Initially, the error was high (~160) but decreased rapidly, stabilizing after 500 iterations. Training was stopped at around 2500 iterations, where further changes were minimal. A learning rate of 0.001 was used throughout the training process.

5. EXPERIMENTAL RESULTS

The datasets were divided into an 80% train set and a 20% test set. The train set was used to train the model using the Darknet-53 framework, which defines the YOLOv3 network. This training was conducted in the Google Collaboratory, an online GPU platform that provides a Tesla K80 GPU with 12GB RAM. The programs utilized for the automatic detection of license plates for non-helmeted motorcyclists were implemented in Python incorporating the OpenCV library. In order to train the YOLO model, approximately 1365 datasets were annotated with bounding box information, including class labels for three distinct classes.

TABLE 1 Precision & Recall Values obtained by Confusion Matrix

	Precision (%)	Recall (%)
With helmet	97.5	91.76
Without helmet	95.07	98.54
Weighted avg	96	95.94

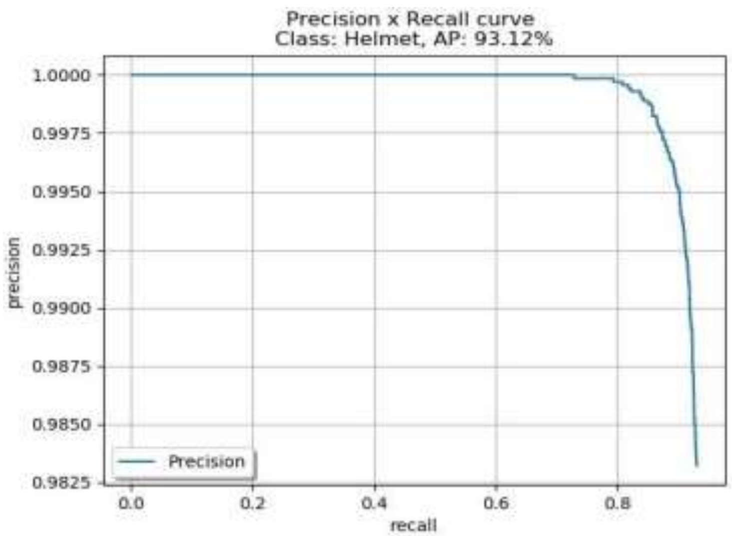

Fig. 6. Recall – Precision Curve

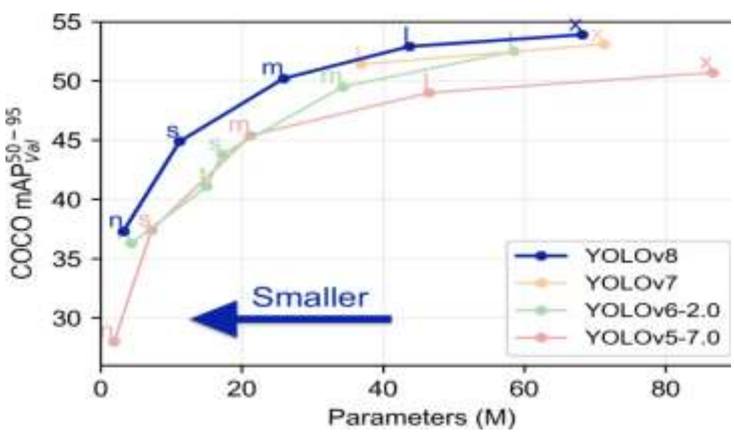

Fig. 7. Comparison of different YOLO Models

The referred fig .5. YOLOv5 was the original version of YOLO, introduced in 2016. It had one stage for object detection. The architecture was based on a single neural network that predicted bounding boxes and class probabilities. YOLOv6 also known as YOLO9000, was introduced in 2016 as an improved version. It introduced anchor boxes to predict different box shapes. This was capable of detecting a large number of objects classesYOLOv7 was introduced in 2018 and brought significant improvements. It included three detection scales and a more complex architecture. YOLOv3 was able to detect a wide range of objects with varying size, figure 6. YOLOv8YOLOv8 was released in 2020, further enhancing accuracy and speed. It introduced several optimizations, including the CSPDarknet53 backbone architecture. YOLOv4 focused on improving real-time object detection performance, figure 7.

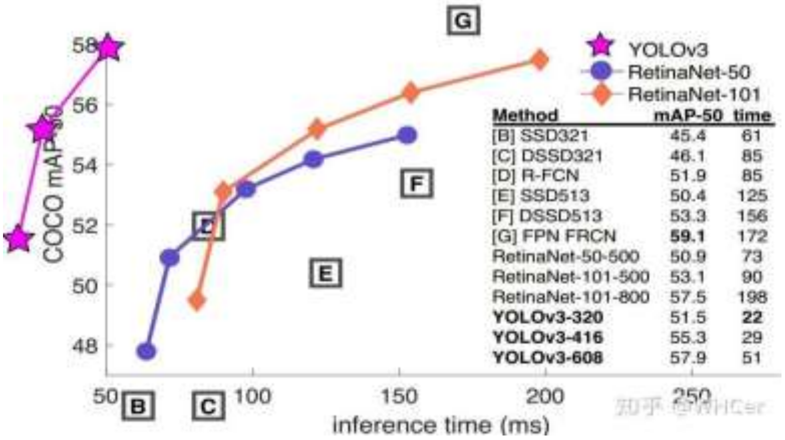

Fig. 7. mAP-50 vs inference time

Real-life license plate detection applications, the balance between Mean Average Precision at 50% intersection over union (mAP-50) and inference time is a critical consideration. mAP-50 is a metric that evaluates the detection system's accuracy, taking into account both precision and recall, refer to figure 7. It is vital in applications where high accuracy and low tolerance for false positives or false negatives are crucial, such as security and compliance-driven scenarios. On the other hand, inference time directly impacts the speed of detection, and faster inference times are essential for real-time or near-real-time applications. Applications that demand quick responses, such as traffic monitoring, toll collection, and access control systems, require low inference times to minimize system latency. Striking the right balance between mAP-50 and inference time is context-dependent. Critical security applications may prioritize mAP-50, even at the expense of slightly longer inference times. In traffic and surveillance scenarios, a reasonable compromise is often sought, while real-time applications may lean towards minimizing inference time, even if it means sacrificing some accuracy. Hardware acceleration can also be employed to improve inference speed. Finding this balance necessitates thorough performance testing and aligning the chosen trade-off with the specific requirements of the license plate detection system at hand.

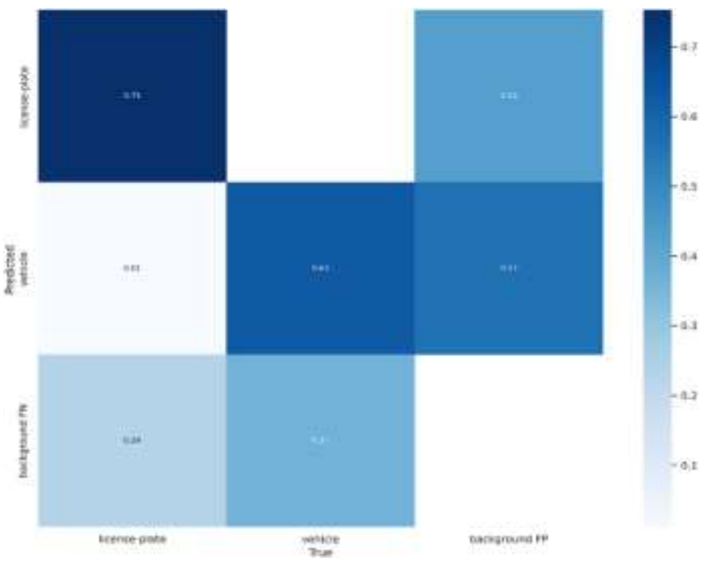

Fig. 8. Confusion Matrix

The figure 8, the confusion matrix results clearly demonstrate that the proposed model outperforms other existing approaches in accurately identifying license plates and vehicles, refer to 8. With a high true positive rate of **75%** for license plates and **63%** for vehicles, the model showcases strong classification capabilities. Moreover, it effectively minimizes false negatives and demonstrates improved robustness in distinguishing objects from complex backgrounds. Unlike traditional methods that often misclassify background elements, the proposed approach significantly reduces such errors, achieving better separation between foreground and background classes. This superior performance highlights the effectiveness and reliability of the proposed model in real-world scenarios, particularly for applications involving license plate recognition and vehicle detection.

6. CONCLUSION

The proposed system demonstrates high reliability in detecting license plates of non-helmeted motorcyclists, even under challenging conditions like obscured headwear. With a remarkable detection accuracy of 98.52%, it effectively balances precision and speed, ensuring minimal false positives while maintaining real-time performance. By accurately identifying traffic violations, the system offers a practical tool for enforcing road safety regulations and reducing accident rates. Its ability to handle diverse scenarios and distinguish subtle visual differences makes it a significant advancement in intelligent traffic monitoring and public safety enhancement.

REFERENCES

[1] Sharma, S. M. (2019). A public health perspective of road traffic accidents. Journal of Family *Medicine and Primary Care*, 8(3), 775–776.

[2] Devadiga, K., Khanapurkar, P., Joshi, S., Deshpande, S., & Gujarathi, Y. (2017). Real time automatic helmet detection of bike riders. International Journal for Innovative Research in Science & Technology, 4(11), 156–160.

[3] Badr, A., Abdelwahab, M. M., Thabet, A. M., & Abdelsadek, A. M. (2011). Automatic number plate recognition system. Annals of the University of Craiova, Mathematics and Computer Science Series, 38(1), 62–71.

[4] Zheng, D., Zhao, Y., & Wang, J. (2005). An efficient method of license plate location. Pattern Recognition Letters, 26(15), 2431–2438.

[5] Du, S., Ibrahim, M., Shehata, M., & Badawy, W. (2013). Automatic license plate recognition (ALPR): A state-of-the-art review. IEEE Transactions on Circuits and Systems for Video Technology, 23(2), 311–325.

[6] Shi, X., Zhao, W., & Shen, Y. (2005). Automatic license plate recognition system based on color image processing. In Lecture Notes in Computer Science (Vol. 3483, pp. 1159–1168). Springer.

[7] Silva, R., Aires, K., Santos, T., Abdala, K., Veras, R., & Soares, A. (2013). Automatic detection of motorcyclists without helmet. In 2013 XXXIX Latin American Computing Conference (CLEI) (pp. 1–7). IEEE.

[8] Huang, D., Shan, C., Ardabilian, M., Wang, Y., & Chen, L. (2011). Local binary patterns and its application to facial image analysis: A survey. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 41(6), 765–781.

[9] Waranusast, R., Bundon, N., Timtong, V., Tangnoi, C., & Pattanathaburt, P. (2013). Machine vision techniques for motorcycle safety helmet detection. In 2013 28th International Conference on Image and Vision Computing New Zealand (IVCNZ) (pp. 35–40). IEEE.

[10] Chiu, C.-C., Ku, M.-Y., & Chen, H.-T. (2007). Motorcycle detection and tracking system with occlusion segmentation. In 2007 IEEE International Conference on Multimedia and Expo (pp. 659–662). IEEE.

[11] Chiu, C.-C., Wang, C.-Y., Ku, M.-Y., & Lu, Y. B. (2008). Real time recognition and tracking system of multiple vehicles. In 2008 11th International IEEE Conference on Intelligent Transportation Systems (pp. 528–533). IEEE

[12] Wen, C.-Y., Chiu, S.-H., Liaw, J.-J., & Lu, C.-P. (2004). The safety helmet detection for ATM's surveillance system via the modified Hough transform. In Proceedings of the 2004 IEEE International Conference on Networking, Sensing and Control (Vol. 1, pp. 557–562). IEEE.

[13] Mistry, J., Misraa, A. K., Agarwal, M., Vyas, A., Chudasama, V. M., & Upla, K. P. (2017). An automatic detection of helmeted and non-helmeted motorcyclist with license plate extraction using convolutional neural network. In Proceedings of the Seventh International Conference on Image Processing Theory, Tools and Applications (IPTA) (pp. 1-6). IEEE.

[14] Redmon, J., & Farhadi, A. (2016). YOLO9000: Better, faster, stronger. arXiv preprint arXiv:1612.08242.