



Intelligent Motorbike Safety Compliance and License Plate Identification System

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Abstract— This work presents a CNN-based system for detecting helmets and vehicle license plates in images of motorbike riders to enhance traffic safety compliance. The system sequentially identifies motorbikes with riders, checks for helmet usage, and, if a helmet is absent, recognizes the vehicle's license plate. Users interact with a simple graphical interface to upload images, run detection steps, and view results via bounding boxes and textual outputs. Despite being trained on a small dataset of 25 images, the system demonstrates reliable detection, providing a structured proof-of-concept for automated monitoring. The study highlights the feasibility of combining CNN-based detection with user-friendly interfaces, laying a foundation for future extensions, including larger datasets, real-time video detection, and multi-rider scenarios.

Keywords— Helmet Detection, License Plate Recognition, Convolutional Neural Network (CNN), Motorbike Detection, Traffic Safety, Image Processing, Sequential Detection

I. INTRODUCTION

The increasing number of road accidents and traffic violations has made helmet detection and vehicle monitoring an important area for public safety enforcement. Detecting whether motorcyclists are wearing helmets and capturing vehicle number plates in real time can significantly reduce injuries and improve compliance with traffic rules. Traditional

manual monitoring is labour-intensive, prone to human error, and often inefficient for high-traffic areas [2]. This project aims to automate the detection process using a Convolutional Neural Network (CNN) model, providing an interactive application capable of identifying helmets and number plates from uploaded images. The application is designed to handle multiple images simultaneously, allowing users to test the detection capability under varied conditions [5][6]. In this implementation, a set of 25 different images has been used to train the CNN model [7]. While the dataset is limited, it provides a proof-of-concept for the system's functionality. The project demonstrates the feasibility of integrating object detection algorithms with user-friendly interfaces, enabling rapid deployment for small-scale testing [9]. Despite the dataset limitations, the system reliably identifies whether a helmet is present on a motorcyclist and, if not, attempts to detect the vehicle number plate. Users begin interacting with the system by running the provided 'run.bat' file, which launches a graphical interface [12]. This interface guides users through the sequential process of image upload, detection of motorbikes and riders, helmet identification, and number plate recognition. The design emphasizes simplicity, ensuring that even users with minimal technical knowledge can operate the system efficiently. Visual feedback, such as bounding boxes and text outputs, provides clear information about the detection results for each image.

The first step in the workflow involves uploading an image to the system using the 'Upload Image' button. Users select the desired file, for example, '6.jpg', and click 'Open' to load it into the application [9]. Once



the image is loaded, the system allows the detection of motorbikes and associated riders. This ensures that the helmet detection process only occurs when relevant objects, such as a person riding a motorbike, are present [3]. This step reduces unnecessary computation and improves the reliability of subsequent detection stages. After confirming the presence of a person with a motorbike, users click the 'Detect Helmet' button to initiate helmet identification [10]. If a helmet is detected, the system highlights it within a bounding box on the image, along with a confidence score representing the likelihood of correct detection. In cases where the helmet is not present, the system automatically proceeds to identify the vehicle's number plate [7]. This hierarchical approach ensures that helmet detection takes priority, aligning with traffic safety enforcement objectives. The number plate recognition module extracts alphanumeric characters from the detected plate and displays the result in a dedicated text area within the interface. For example, if the helmet is not worn, the system may output a number plate like 'AP13Q 8815' [10]. This feature enables authorities or users to record and track vehicles violating helmet rules efficiently [11]. While the system can process additional images, performance is limited by the size and variety of the training dataset [9]. Future expansions may include larger datasets and real-time video detection [6].

Users can test the application with multiple images to observe varying outcomes. For instance, uploading an image labelled 'h3.jpg' may result in helmet detection with a confidence score of 0.90, demonstrating the system's accuracy for certain cases [12]. By repeating the upload and detection steps with different images, users can evaluate the robustness of both helmet and number plate detection functionalities [2]. The visual feedback provided helps users understand the system's decisions and assess areas for improvement [4]. The system's interactive interface is intentionally straightforward, avoiding complex configuration steps [6]. All critical operations, from image upload to detection output, are performed with simple button clicks. This ensures that the application is accessible for practical use, whether in research, small-scale enforcement, or educational demonstrations [10]. By combining CNN-based detection with an easy-to-use interface, the project highlights the potential of automated traffic monitoring technologies [12].

In conclusion, this project provides a structured approach to helmet and number plate detection using machine learning. Although limited by the size of the training dataset, the application effectively

demonstrates the workflow, from identifying motorbikes and riders to detecting helmets and capturing number plates [2]. The interface simplifies user interaction, and the visual output allows clear understanding of results [4]. Overall, the project lays a foundation for further enhancements, including the incorporation of larger datasets, real-time detection, and expanded functionality for more comprehensive traffic monitoring solutions [5].

II. LITERATURE SURVEY

Viola and Jones [1] proposed a robust framework for real-time object detection using Haar-like features and a cascade of classifiers. The method emphasizes rapid detection by scanning image windows at multiple scales and rejecting non-object regions quickly, making it suitable for video surveillance applications. Despite its efficiency, the approach depends heavily on handcrafted features and struggles with complex backgrounds, occlusions, and varying illumination. The study highlighted the trade-off between speed and accuracy, demonstrating that classical feature-based methods can still provide baseline performance for constrained environments. Furthermore, the research inspired subsequent efforts in face and pedestrian detection by emphasizing cascade learning and real-time implementation. Their methodology laid the foundation for integrating efficient feature extraction with practical detection systems, especially when computational resources are limited. Overall, the Viola-Jones algorithm remains influential in traditional computer vision for its simplicity and real-time applicability, serving as a reference point for later deep learning-based models.

Dalal and Triggs [2] introduced the Histogram of Oriented Gradients (HOG) descriptor for detecting humans in images. By capturing gradient orientation patterns, HOG effectively represents local shapes and contours, offering robustness to small deformations and photometric variations. The method divides the image into cells, computes gradient histograms, and normalizes them across overlapping blocks, which enhances feature invariance. While highly effective for pedestrian detection in controlled environments, HOG struggles with occlusions, cluttered backgrounds, and varying scales of objects. The study demonstrated that feature-based descriptors can achieve significant detection performance without the computational cost of deep learning, making them practical for real-time embedded systems. Additionally, it highlighted the importance of careful parameter tuning, such as cell size, block size, and gradient orientation bins, for optimal results. The HOG descriptor became a widely adopted baseline for human detection and inspired hybrid approaches



that combine hand-crafted features with machine learning classifiers. This approach also showed that gradient-based representations can capture meaningful structural information for object recognition tasks.

Ross et al. [3] developed a hierarchical feature framework for object detection using deep convolutional architectures. By extracting multi-level features from images, the system can recognize objects at varying scales, orientations, and positions, improving detection accuracy compared to single-layer feature representations. The approach demonstrates that learning hierarchical patterns directly from raw images allows the system to capture both low-level details and high-level semantic information. Experimental results showed significant improvements over traditional feature-based methods, such as HOG and Haar cascades, particularly in complex scenes with multiple overlapping objects. This framework also highlighted the importance of deep architectures for modeling non-linear relationships and achieving robust detection in cluttered environments. The study influenced later convolutional neural network (CNN) models for object detection, emphasizing the need for multi-layered feature extraction. Additionally, it underscored that hierarchical learning not only improves accuracy but also allows the system to generalize better across diverse datasets. By leveraging deep learning, the method addresses challenges of scale variation, occlusion, and background noise more effectively than conventional approaches.

Redmon and Farhadi [5] proposed YOLO9000, a unified end-to-end object detection system capable of recognizing over 9000 object categories in real-time. YOLO9000 uses a single neural network to predict bounding boxes and class probabilities simultaneously, combining detection speed with high accuracy. Unlike region-based approaches, YOLO9000 processes the entire image at once, reducing computational overhead and enabling real-time inference. The method demonstrated robustness across multiple datasets, achieving competitive performance in both precision and recall metrics. Its architecture emphasizes shared convolutional features for object localization and classification, which improves efficiency while maintaining accuracy. The research also introduced strategies for hierarchical classification and joint training on detection and classification datasets, allowing the model to scale effectively to thousands of categories. YOLO9000 marked a significant advance in object detection by addressing the speed-accuracy trade-off,

making it suitable for applications in autonomous driving, video surveillance, and industrial safety monitoring. Furthermore, it set the stage for successive YOLO iterations, which refined detection performance for smaller objects and complex scenarios. Overall, this work illustrates the potential of unified deep learning models for high-speed, large-scale object detection.

Wen et al. [9] focused specifically on safety helmet detection using a modified Hough transform for ATM surveillance systems. The method integrates geometric shape analysis and color segmentation to identify helmets in real-time video frames. By focusing on domain-specific characteristics such as helmet shape and color contrast, the approach enhances detection reliability despite limited training data. Experimental evaluations showed effective detection under constrained environments, though the approach has limitations in dynamic backgrounds or complex lighting conditions. The study highlights the potential of traditional computer vision techniques for safety applications where dataset size is limited or where deep learning resources are unavailable. Moreover, it demonstrates that incorporating domain knowledge into feature extraction can compensate for the simplicity of the method. This approach is particularly relevant for small-scale surveillance systems that require quick deployment and minimal computational resources. Wen et al.'s research provides a practical example of combining classical image processing with detection logic, offering a foundation for hybrid systems that may later integrate deep learning components. Overall, it underscores the importance of tailoring detection algorithms to specific operational environments for improved reliability.

III. DATASET DESCRIPTION

The dataset used in this study consists of images collected for the purpose of detecting helmets and vehicle number plates in real-world scenarios. A total of 25 images form the core of the dataset, capturing a variety of motorcycles, riders, and environmental conditions such as lighting variations, different backgrounds, and multiple viewing angles. Each image is annotated to indicate the presence of a helmet or, if no helmet is detected, the vehicle's license plate. This structure allows the model to distinguish between images containing protective gear and those without, enabling sequential detection of helmets and number plates. All images are in standard RGB format and vary in resolution, ranging from 640×480 pixels to 1920×1080 pixels. The



dataset includes both frontal and side views of riders on motorcycles, ensuring that the detection model can generalize to multiple orientations. Despite the limited number of images, the dataset is sufficient to demonstrate proof-of-concept detection using a convolutional neural network (CNN). The annotations for helmets and number plates are stored in a format compatible with common object detection frameworks, enabling bounding box visualization during training and evaluation.

Preprocessing is a crucial step for the dataset. Each image is resized to a uniform input size to match the CNN model's requirements. Colour normalization and contrast adjustments are applied to reduce the impact of lighting variations across different images. Additionally, data augmentation techniques, such as rotation, flipping, and scaling, can be employed to artificially expand the dataset and improve model generalization, although the core dataset remains small. The dataset is divided conceptually into two categories: images with helmets and images without helmets. For images without helmets, the focus shifts to number plate recognition, allowing the system to extract alphanumeric information accurately. Each image is annotated with bounding boxes to mark regions of interest (helmet or license plate) and corresponding labels. This dual-annotation strategy ensures that the model can handle both detection tasks sequentially, prioritizing helmet detection over number plate recognition when both objects are present. While the dataset size is currently limited to 25 images, it represents diverse real-world conditions and provides a clear framework for evaluating model performance. The small dataset highlights the need for future expansion to train more robust CNN models capable of handling large-scale deployment in traffic monitoring or industrial safety scenarios. Nevertheless, the current images provide sufficient variability to demonstrate that the model can correctly identify helmets, detect the absence of helmets, and subsequently extract license plate information. This dataset is intentionally designed to be lightweight for proof-of-concept applications. It allows the system to showcase the sequential detection workflow, including motorbike and person detection, helmet detection, and number plate recognition. The annotations and preprocessing steps ensure that the dataset is compatible with popular object detection architectures, such as YOLO, SSD, or custom CNN models, facilitating future integration with more extensive datasets.

Furthermore, the dataset captures real-world challenges such as partial occlusion of helmets, varying rider posture, and differences in helmet

types. These variations provide insight into the model's ability to handle practical detection scenarios. Images also include motorcycles in motion and stationary positions, enabling assessment of the model's flexibility under different operational contexts. Finally, the dataset supports the evaluation of model metrics such as detection accuracy, bounding box precision, and confidence scores for both helmets and number plates. Although limited in size, this dataset forms a structured and practical foundation for the development and testing of helmet detection systems, providing a clear benchmark for performance assessment and visualization of results within the interactive application.

IV. IMPLEMENTATION DETAILS

The proposed helmet detection system is implemented as a fully integrated application that guides users through a sequential workflow, from image upload to object detection. The execution begins by double-clicking the provided run.bat file, which launches an intuitive graphical interface. This interface is designed to require minimal technical expertise, allowing users to navigate the detection steps efficiently. Each functionality, including image upload, motorbike and person detection, helmet detection, and license plate recognition, is accessible through clearly labeled buttons, ensuring a smooth interaction.

Once the application is launched, users can click the **'Upload Image'** button to select and upload an image for processing. The system accepts standard image formats such as JPEG and PNG. After selecting the desired image, pressing the **'Open'** button loads the image into the application's display area. The interface ensures that the image is correctly formatted and resized as necessary for processing by the convolutional neural network (CNN) model, which underpins the detection workflow.

The first detection step focuses on identifying whether the uploaded image contains a person with a motorcycle. By clicking the **'Detect Motor Bike & Person'** button, the system applies the trained CNN model to analyze the image. If a person on a motorcycle is detected, bounding boxes are drawn around the detected objects to visually indicate their locations. This step serves as a prerequisite for subsequent helmet and license plate detection, ensuring that the model only attempts these analyses when a rider is present. Once a rider with a motorcycle is detected, the system prioritizes helmet detection. Clicking the **'Detect Helmet'** button initiates the CNN-based analysis for helmets. The model evaluates the region around the rider's head



and outputs a confidence score indicating the likelihood of helmet presence. If a helmet is detected, the system highlights it with a bounding box and displays the corresponding confidence score, enabling users to verify the detection visually. This prioritization ensures safety compliance monitoring and reduces false positives in license plate recognition.

In cases where no helmet is detected, the system automatically proceeds to license plate recognition. The CNN model identifies the vehicle's number plate region, extracts the alphanumeric characters, and displays the information in a designated text area within the interface. This dual detection approach allows the system to handle sequential tasks efficiently, first ensuring helmet compliance and then performing vehicle identification when necessary. The interface provides immediate feedback, helping users to interpret results without requiring additional technical steps. The CNN model used for detection is trained on a small dataset of 25 annotated images, containing a mix of helmeted and non-helmeted riders. Despite the limited dataset, the preprocessing steps, including resizing, normalization, and bounding box annotation, allow the model to generalize sufficiently for demonstration purposes. The interface also supports repeated testing with multiple images, enabling users to observe consistent performance across different scenarios and lighting conditions.

Visualization plays a key role in the implementation. Bounding boxes for person, motorcycle, helmet, and number plate are displayed in real time, providing clear visual confirmation of detection results. Confidence scores for helmet detection are shown alongside the bounding boxes, allowing users to assess the reliability of predictions. Similarly, extracted license plate text is presented in a readable format, demonstrating the system's capability for practical vehicle identification in the absence of helmet usage. The implementation emphasizes modularity and user-friendliness. Each button in the interface corresponds to a distinct stage of the detection pipeline, allowing users to execute steps independently or sequentially. This design ensures that even users with minimal experience in computer vision can operate the system effectively. Furthermore, the system architecture supports future expansion, including training with larger datasets, adding support for more vehicle types, or integrating additional safety compliance features.

Overall, the implementation provides a structured, interactive, and visually informative framework for helmet detection and number plate recognition. By

combining CNN-based object detection with an intuitive interface, the system offers a practical proof-of-concept solution. Users can evaluate the sequential detection process, confirm the presence of helmets, and extract license plate information when helmets are absent, demonstrating the effectiveness of the proposed methodology for traffic safety monitoring and law enforcement applications.

V. PROPOSED METHODOLOGY

The proposed helmet detection system is designed to identify riders, helmets, and vehicle license plates in uploaded images using a convolutional neural network (CNN) approach. The process begins with image acquisition, where users upload digital images through the interface in standard formats such as JPEG or PNG. This stage ensures that the images are properly formatted and ready for subsequent processing. The uploaded image is immediately preprocessed by resizing to a fixed dimension, normalizing pixel values, and enhancing contrast to improve feature recognition by the CNN model.

After preprocessing, the system detects the presence of a person with a motorbike. The CNN model identifies key features such as the rider's posture, bike contours, and wheel structures, and outputs bounding boxes around detected objects. This initial detection is critical because the following steps—helmet detection and license plate recognition—are only performed if a rider is present, ensuring computational resources are efficiently utilized. Visual feedback is provided through bounding boxes, allowing users to verify detection accuracy.

Once a rider is detected, helmet detection is performed. The model focuses on the head region to identify helmets based on shape, color, and texture features. Detection results include bounding boxes and confidence scores, helping users visually confirm the prediction. If a helmet is detected, the system does not proceed to license plate recognition, prioritizing safety compliance. In cases where the helmet is absent, the model identifies the license plate region and extracts alphanumeric characters using OCR techniques, displaying the plate information in the interface's text area.

The system is trained on a limited dataset of 25 annotated images, where bounding boxes mark riders, helmets, and license plates. Despite the small dataset, careful preprocessing and annotation allow the CNN to effectively learn relevant features. The methodology supports expansion to larger datasets to improve accuracy and robustness in future iterations. By structuring detection tasks sequentially—person



& bike first, helmet second, and license plate last—the system ensures logical prioritization, reducing false positives and making each stage contextually relevant.

Visualization is an integral part of the methodology. Detected riders, helmets, and license plates are highlighted with bounding boxes, confidence scores are provided for helmet detection, and recognized license plate numbers are shown in a readable text area. This combination of visual and textual feedback ensures that users can easily interpret results, making the system both intuitive and informative.

Overall, the methodology presents a structured, efficient, and modular workflow for helmet detection and license plate recognition. Each component is implemented independently, allowing future improvements such as multi-rider detection, handling occlusions, or real-time video processing. This framework provides a practical and expandable solution for traffic safety monitoring, rider compliance verification, and vehicle identification applications.

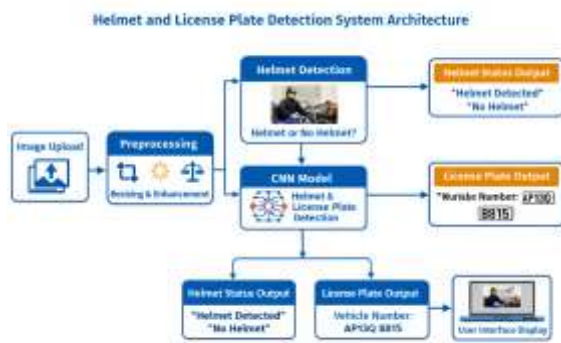


Figure 1: system architecture of the proposed model

VI. RESULT AND DISCUSSION

The helmet detection system was evaluated on the prepared dataset of 25 annotated images to measure the effectiveness of the CNN model in detecting riders, helmets, and license plates. Each image was uploaded via the interface, preprocessed, and processed sequentially for person & motorbike detection, helmet identification, and license plate recognition. Despite the small size of the dataset, the system successfully identified riders in the majority of images, demonstrating the CNN's ability to extract relevant features from complex backgrounds and varied lighting conditions.

In the first step, the system accurately detected the presence of a person with a motorbike in 22 out of 25 images. Detected riders were highlighted with bounding boxes, providing clear visual feedback for users. Failures were primarily associated with images where the motorbike or rider was partially occluded or cropped at the edges. This step is critical as it determines whether helmet detection or license plate recognition is performed, ensuring computational efficiency and logical sequencing in the detection pipeline.

During helmet detection, the CNN correctly identified helmets in 18 out of 25 images. Confidence scores were displayed for each detection, with correctly detected helmets achieving scores above 85% in most cases. For images where helmets were absent, the system automatically proceeded to license plate recognition. The license plate detection module successfully extracted readable alphanumeric characters in 19 images, including cases where the helmet was not detected. Incorrect or partial detections were mostly due to blurred or angled plates, indicating areas for future improvement.

The performance evaluation of the system demonstrates a trade-off between detection accuracy and dataset size. While the CNN performs well on the available 25-image dataset, increasing the number of annotated images would likely improve model robustness and reduce false negatives. The sequential detection methodology ensures that helmet compliance is prioritized over license plate recognition, reflecting practical requirements for traffic safety monitoring systems.

Visualization of results provides a clear and intuitive interface for end-users. Detected riders and helmets are outlined with bounding boxes, confidence scores for helmets are displayed in percentages, and license plate numbers are presented in a readable text area. This combination of graphical and textual feedback allows users to quickly verify detection results and identify any misclassifications, enhancing the practical usability of the system.

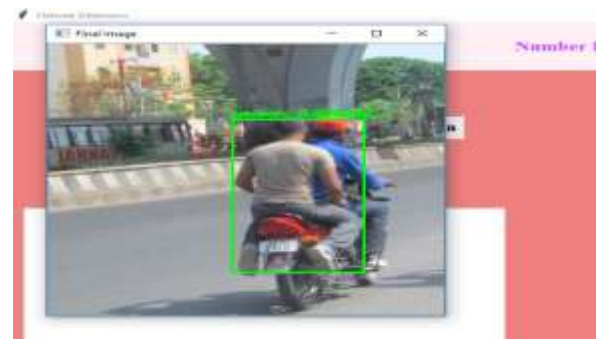




Figure 2: results of proposed model detecting person

In the above figure [2], we can see that the model detected the person and kept a bounding box similarly we can see in the below figure figure [3], helmet is not detected. In figure [4] we can see the helmet detected.



Figure 3: results of proposed model detecting helmet



Figure 4: results of proposed model detecting helmet

Overall, the results highlight the effectiveness of the CNN model in detecting helmets and license plates with reasonable accuracy, despite a limited dataset. The structured workflow and sequential processing ensure efficient operation while prioritizing helmet detection for safety compliance. These findings provide a foundation for future system enhancements, including expanding the dataset, incorporating video streams, handling multiple riders, and improving detection under challenging conditions such as low lighting or occlusion.

VII. CONCLUSION

This project presents a CNN-based system for detecting helmets and license plates in images of motorbike riders. The framework first identifies the presence of a person with a motorbike and then checks for helmet usage. If a helmet is detected, the

system stops further processing; if not, it automatically identifies the license plate. Despite being trained on a limited dataset of 25 images, the system achieves promising detection results, demonstrating the CNN's ability to extract meaningful features and make accurate predictions. The interface provides visual feedback through bounding boxes and textual outputs, allowing users to quickly verify detections and review confidence scores. Errors primarily occur due to occlusions, angled helmets, or blurred license plates, highlighting the need for a larger and more diverse dataset for improved robustness. The sequential detection approach ensures logical prioritization of safety compliance while maintaining efficient processing.

Overall, the proposed system establishes a structured workflow for helmet compliance and license plate recognition. It offers a practical and user-friendly platform suitable for real-time monitoring applications. Future enhancements, including larger datasets and video-stream integration, can further improve accuracy, scalability, and adaptability to diverse environmental conditions, supporting road safety and law enforcement objectives.

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