Multi-Model System for Enhanced Road Safety: A Deep Learning Approach

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Abstract: - In view of the increasing number of accidents and fatalities on the roads, the need for the application of automatic road safety surveillance has also increased. The paper proposes a multi-model system for improved road safety, wherein deep learning models, primarily based on Convolutional Neural Networks (CNN), are used for the enforcement of critical safety parameters. The parameters include helmet usage, seat belts, lane discipline, and face mask usage. The proposed research is based on the development of individual detection models. However, the models are made to run either individually or in parallel, thereby ensuring real-time checking for the enforcement of the aforementioned parameters in the presence of demanding vehicles and conditions. The proposed model, despite being based on real-time operation, has the advantage of ensuring ease of operation without the requirement for excessive computation, thus helping law enforcement agencies in pursuing violators for the aforementioned offenses.

Key-Words: - Road safety, Real-time monitoring, Traffic control, Convolutional neural networks, Deep learning, Multi-model system.

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1 Introduction

The road safety problem is of global concern as every year, many fatalities occur due to road accidents, and many suffer injuries as victims of such accidents, [1]. This problem is even worse in countries such as India because of vehicle overload, non-enforcement of rules, and non-compliance with road safety rules by citizens, [2]. Studies have proved time and again that road safety rules such as lane discipline, wearing helmets, strapping seat belts, etc., can help in reducing road fatalities and injuries, [3], [4].

This research shows that strict enforcement and adherence to safety regulations significantly reduce the likelihood of fatal injuries. Helmet detection is one example, where object detection algorithms like those in YOLOv5 or YOLOv7 have improved motorcyclist safety, [5], [6], [7]. Furthermore, seat belt detection systems have demonstrated the efficacy of CNN-based systems and other deep learning image classifiers against poor lighting and occlusion, [8], [9], [10].

Lane discipline detection is another crucial component in reducing collisions and encouraging smooth traffic flow, [11], [12], [13]. CNN-based models, Hough transforms, and edge detection techniques have produced remarkable results in lane adherence monitoring, [14], [15]. In the post-pandemic world, face mask detection is also becoming more and more popular, especially for shared mobility and public transportation applications, [16]. The SSD and MobileNetV2 models are equally effective for this purpose.

The multi-model system for advanced road safety is necessary, [17]. With respect to a single task system, the architecture offers great flexibility and scalability by enabling the fine-tuning and deployment of any of its models, such as seat belts, helmets, masks, or lanes, either independently or in parallel, [18], [19], [20]. As a part of the system that can be deployed in both urban and rural environments and is flexible enough to accommodate different kinds of traffic and vehicles, the system also supports video analysis through APIs in real time to facilitate feedback and active monitoring, [21], [22]. The law enforcement organizations can make use of this framework to automate the process of compliance, thereby reducing the need for manual labor and increasing the coverage of the monitoring process, [23], [24].

In the context of the manual process of the above measures, there are enormous challenges, which have resulted in the occurrence of many violations and the safety of the public being at risk. Proposing the multi-model system for the improvement of road safety is the objective of this paper, in which the alignment of multiple models using deep learning technology with the aid of Convolutional Neural Networks (CNNs) will work towards identifying the behavior of compliance for assets like seat belts, helmets, face masks, and lanes.

2 Prior Art in Vision-Based Road Safety Monitoring

Recent developments in computer vision and artificial intelligence have given automated road safety enforcement more options. Specifically, the CNNs are perfect for identifying safety violations in image recognition and object detection tasks since they have demonstrated exceptional efficacy in complex image recognition tasks, [14], [15]. Currently, models are being used to automatically monitor compliance with safety actions like wearing masks, seat belts, helmets, and lane discipline.

2.1 Automatic Helmet Violation Detection

Motorcycle riders wearing helmets have fewer head injuries in case of an accident. Various studies have developed CNN-based systems that incorporate the use of video surveillance for the automatic detection of helmets. Some authors proposed a real-time system to detect bike riders without helmets through surveillance videos, and 93.8% accuracy is achieved through efficient processing, [18]. One computer vision approach for seat belt detection uses a window detection, a refined detection using face detection, and belt detection using connected components. This approach has higher accuracy than previous approaches, [5].

More recently, Saravanan and Rajini employed state-of-the-art machine learning in 2024 to demonstrate automated helmet violator detection systems that perform better in a range of traffic and lighting conditions, [7]. Further proof of the efficiency of progressive object detection models for applications like helmet detection comes from comparative studies of YOLOv5, YOLOv6, and YOLOv7 variants, [6].

It also demonstrates that the deep learning models, which are based on the CNN and YOLO algorithms, perform satisfactorily and could therefore serve as an effective model for carrying out the test of helmet detection in urban traffic scenarios.

2.2 Visual Detection of Seat Belt Compliance

Wearing seat belts is very important for safety, particularly in situations where there is a strong possibility of an accident occurring. In a major study, for instance, some authors proposed a vision-based system for detecting whether drivers and passengers are wearing seat belts using a CNN. A computer vision technique for seat belt detection involves window detection, face detection for more accurate window detection, and connected components for seat belt detection. It provides more accurate results than existing techniques, [3]. A deep learning–based method using CNN and SVM improves seat belt detection accuracy in complex traffic scenes, [9], proving superior real-time processing capabilities and perfect generalization to other models of vehicles, [16]. Thus, the results prove the efficiency of deep learning models concerning monitoring seat belt usage, thereby reducing dependence on continuous monitoring by human surveillance and promoting the efficiency of automatic traffic enforcement systems.

2.3 Lane Departure and Adherence Detection Techniques

Excessive collisions would be averted, and appropriate traffic flow would be guaranteed if lane discipline were carried out. Over time, though lane detection was originally based on techniques such as the Hough Transforms and Canny edge detection, there has been a paradigm shift towards CNN-driven and machine learning techniques. For instance, some authors worked to understand the problem of lane boundary detection under various road conditions and thereby proposed a model comprising edge detection and region of interest filtering. Their real-time application demonstrated good occlusion and image noise tolerance, [11].

Farag and Saleh presented an enhanced version of the real-time lane line detection system for ADAS to improve its accuracy in dynamic traffic situations by implementing these techniques, [13]. Another study performed road boundary detection along with continuous lane tracking using supervised learning with video input features, [12]. Further, a few authors proposed an algorithm for lane departure detection in an intelligent vehicle using a CNN, proving that the CNN offers high-reliability classification for vehicle safety systems, [21]. These studies prove that deep learning performs better in comparison with conventional techniques of lane road tracking compliance, but especially when real-time and unexpected variation arises.

2.4 Real-Time Face Mask Monitoring in Transit Environments

The past pandemic situation has proven that it is necessary to monitor face mask wear, especially in public spaces and transportation systems. The process of tracking face masks is being replaced by deep learning to fully automate it, based on object detection and classification. A machine learning-based face mask detection system using MobileNetV2 and SSD is proposed to detect masked and unmasked people in public areas and monitor COVID-19 safety, [16].

Some authors have also proposed more advanced approaches, which are based on the transfer learning of the CNN algorithm, to prove that the detection of personal protective equipment can be done very accurately in real-life scenarios by tuning the pre-trained models, [16].

The hybrid models of the CNN algorithm have also been tested to improve the detection of the images, considering the different angles, face orientations, and lighting conditions, to ensure the consistency of the detection of the challenging datasets, [16], [20]. The advances in deep learning models for the detection of face masks have increased the viability of the models, thereby enhancing their usefulness for health and safety in transit.

3 Process Flow of the Proposed System

The flow chart of the proposed multi-model system design to enhance road safety has defined a clear series of operations that begin with data acquisition and end with compliance reporting. The workflow thus allows for the end-to-end real-time monitoring and analysis of vital parameters regarding road safety through stages of dependency. Figure 1 shows the data preprocessing workflow for multimodal datasets. The process begins with real-time data acquisition through continuous video capturing from fixed roadside surveillance cameras. The videos will be broken down into individual frames for analysis. Each of these frames will now undergo image preprocessing: resizing, denoising, and normalizing to enhance clarity and consistency. The Region of Interest (ROI) is extracted. It is a task to isolate specific areas from every frame based on the detection task, e.g., a face region is segmented for the detection of face mask, upper torso for helmet and seat belt usage, and road surface for lane discipline monitoring. After that, applying further techniques in image enhancement, such as edge detection and sharpening, improves the visibility of the features within these regions.

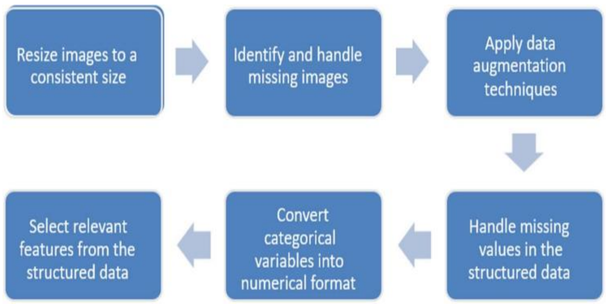

Fig. 1: Data Preprocessing Workflow for Multimodal Datasets
Source: created by the authors

Figure 2 shows the flowchart of the development pipeline for a transfer learning-based CNN. Then, after preprocessing, the output ROIs or full frames are fed into a collection of deep learning models based on CNNs and explicitly designed for detecting a principal compliance factor feature. To illustrate, the face mask detection model analyzes facial features and makes decisions about their usage, while the helmet detection model checks if the motorcycle riders are wearing helmets. Moreover, the lane adherence model scrutinizes the positioning of a vehicle to lane markings. Such that, the seat belt detection model ascertains whether the passengers have fastened their seat belts. These models are optimized through pruning and lightweight architecture to ensure a speedy inference that is optimal for real-time applications.

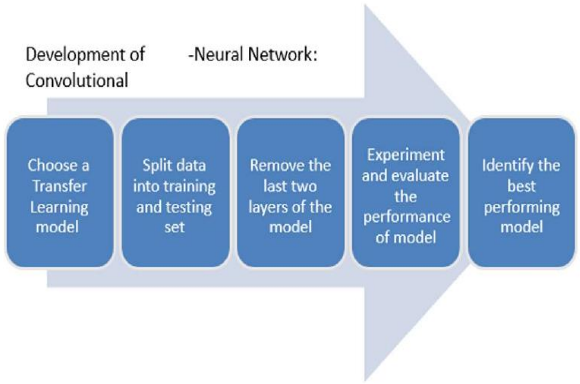

Fig. 2: Development Pipeline for Transfer Learning-Based Convolutional Neural Network
Source: created by the authors

After getting the output from individual detection models, all of them are directed into one central stage of compliance aggregation and decision logic. At this stage, a decision engine aggregates these individual results to generate a comprehensive compliance report for every processed frame. From such an approach, all compliance parameters will be evaluated and labeled compliant or non-compliant according to the model's prediction.

Once a violation is found, it will trigger the system to come up with on-time alerts containing vital information like violation type and timestamp, as well as an image of the particular occurrence. The alerts are recorded in a central database but may be forwarded to relevant enforcement authorities using Application Programming Interfaces (APIs) for auto e-ticketing or intervention.

3.1 Mathematical Formulation of the Multi-Model CNN Framework

We formulate the proposed road safety monitoring architecture as an ensemble of independent deep learning models. Each detection task is modeled as a supervised binary classification based on Convolutional neural networks.

Each frame is represented as a 3-D tensor as given in equation (1)

$$X \in \mathbb{R}^{\{H\times W\times C\}} \tag{1}$$

where H and W denote Height and width of the frame and C represents Color channels for each compliance task $i \in \{1,2,\dots,M\}$ a deterministic region of interest, with extraction function $Ri(\cdot)$ defined as in equation (2)

$$X_i = R_i(X) \tag{2}$$

This ROI-based decomposition guarantees that each model processes only pertinent visual content, where represents a reduced spatial input. This spatial restriction enhances stability in training and optimization problems by reducing dimensions in feature spaces, thwarting unnecessary gradients in propagation. Non-linear mapping is the definition of each CNN model, respectively represented by equation (3):

$$f_i(X_i;\theta_i) \to p_i \tag{3}$$

The trajectory of its task optimizations is not influenced by any competing gradients coming from other tasks due to parameter space separation. where θi denotes the learnable parameters of model i and pi ∈ [0,1] represents the predicted probability of a safety violation. The outputs of all models are aggregated into a single prediction vector as given by equation (4):

$$p = [p_1, p_2, \dots, p_M] \tag{4}$$

$$\hat{y}_i = \begin{cases} 1, & p_i \geq \tau_i \\ 0, & p_i < \tau_i \end{cases}$$

Loss Function as given by equation (5):

$$\mathcal{L}_i = -[y_i \log(p_i) + (1-y_i)\log(1-p_i)] \tag{5}$$

Total Loss as given by equation (6):

$$\mathcal{L}_{total} = \sum_{i=1}^{M} \mathcal{L}_i \tag{6}$$

Since each loss term depends exclusively on its corresponding parameter set θ_i , The global optimization objective decomposes into independent sub-problems, allowing each model to be optimized without interference from other tasks.

Unlike conventional multi-task learning approaches that depend on a shared feature extraction backbone and often require task-specific loss weighting to address gradient dominance, the proposed system is designed around independent parallel training. Each CNN model is trained separately on its own task-specific Region of Interest (ROI), ensuring that the learning dynamics of one task do not interfere with others. As a result, each task is assigned equal loss weights ($\lambda_i = 1$), as the absence of shared parameters eliminates gradient dominance and preserves independent convergence behaviour across tasks, is represented by by equation (7) and equation (8):

$$\mathcal{C}_{multi} = \sum_{i=1}^{M} F_i \tag{7}$$

where:

$$F_i = O(h_i w_i K^2 d_i) \tag{8}$$

M denotes the number of task-specific CNN models in the proposed framework, corresponding to helmet detection, seat belt detection, lane adherence monitoring, and face mask detection. and

F_i represents the number of floating-point operations (FLOPs) required by the i-th CNN model during inference and let $T_i$denote its corresponding inference latency. The total computational cost of the proposed multi-model framework. Since all task-specific models operate independently and are executed in parallel, the effective real-time inference latency of the system is governed by the slowest model, which is expressed as in equation (9)

$$T_{parallel} = \max(T_1, T_2, \dots, T_M) + \tau_{overhead} \quad (9)$$

For real-time safety enforcement applications, this bound offers a deterministic upper limit on system latency. A shared deep backbone would be necessary for a single unified multitask CNN architecture, which would have the following computational cost, as expressed in equation (10)

$$\mathcal{C}_{single} = F_{shared} + \sum_{i=1}^{M} F_{head,i} \quad (10)$$

where represents task-specific prediction heads and corresponds to the shared feature extraction layers. Large receptive fields and dense intermediate feature representations cause it to dominate the total FLOPs in real-world deployments. The efficiency requirement is met by the suggested architecture, as illustrated in equation (11):

$$C_{ours} = \sum_{i=1}^{M} O(h_i w_i K^2 d_i) + C_{ROI} + C_{merge} \quad (11)$$

Instead of processing the entire image frame, each CNN model processes a spatially constrained Region of Interest (ROI), greatly lowering the computational load per task while preserving scalable deployment and predictable inference latency. Compared to monolithic multi-task models, the suggested multi-model framework achieves reduced computational coupling, better scalability, and lower effective inference latency. making it appropriate for monitoring road safety in real time in environments with limited hardware.

4 Performance Evaluation of the Multi-Model System

A composite dataset selected from publicly accessible annotated image repositories for helmet, lane discipline, seat belt, and face mask detection was used to assess the suggested multi-model system. By including images taken in a range of lighting conditions, from bright daylight to moderately low light, the dataset specifically addresses the sensitivity issues related to illumination and occlusion. The total dataset contains 14,500 annotated images. The system's performance, in particular local transit scenarios, was tested using the public data for the helmet, seat belt, and face mask modules. An 80% training set and a 20% testing set were created from the images. The models were trained and fine-tuned using the Google Colab Pro platform, utilizing high-performance NVIDIA T4 GPUs to accelerate the training of the CNN architectures. The training configuration and hyperparameters are illustrated in Table 1.

Table 1. Training Configuration and Hyperparameters

Learning Rate	0.001
Batch Size	32
Epochs	50
Optimizer	Adam
Dataset Size	14,500 images

Source: created by the authors

4.1 Helmet Detection

The average accuracy of 94% has been achieved for the helmet detection module for both urban and suburban test cases. The CNN has been used to classify the images into helmeted and non-helmeted riders, as shown in Figure 3 and Figure 4.

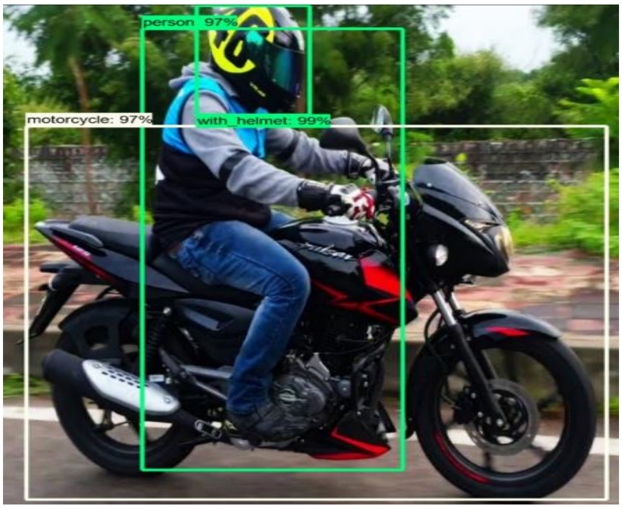

Fig. 3: Detection of helmet usage using a CNN-based helmet detection model under varying illumination conditions, including daylight and motion blur scenarios. The model accurately localizes motorcyclists and identifies helmet usage despite background clutter and illumination variations. The correct bounding box alignment around the rider's head region demonstrates robust feature extraction and generalization capability

Source: created by the authors

Fig. 4: Comparison of helmet detection results between compliant and non-compliant riders. The model successfully distinguishes helmet-wearing riders with reliability

Source: created by the authors

4.2 Seat Belt Detection

The model for detecting seat belts has been performing at an average of 92%, differentiating seat belts for occupants and those without, as illustrated in Figure 5. Apart from using CNNs and existing pre-trained models for sound performance in most lighting conditions, partial occlusions may still be a challenge, especially when the seat belt color is similar to that of dark clothing fabric.

Fig. 5: Detection of seat belt usage using CNN, showing correct and incorrect use in vehicles

Source: created by the authors

4.3 Lane Adherence Monitoring

The module for adhering to the lane, which detects lane departure, performed at an average of 90% metric for both conditions on highway and city road environments. The module can detect lane boundaries and hence is very effective for traffic monitoring.

4.4 Face Mask Detection

The model for detecting face masks performed at 95% accuracy for controlled and real conditions. In a crowded scene, the identification of masked and unmasked persons is possible, as illustrated in Figure 6.

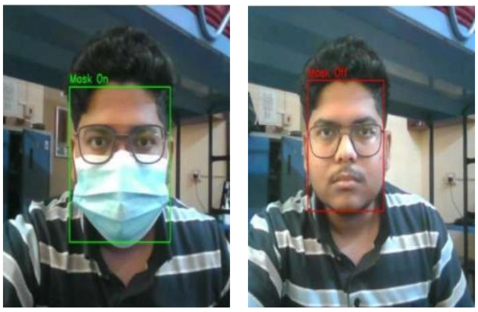

Fig. 6: Detection of face mask using CNN

Source: created by the authors

4.5 Overall System Performance

The ensemble of the Multi-Model Systems was able to achieve an average of 92.75% overall accuracy on all the compliance tasks, an extremely high level of processing speed, and was very modular. Figure 7 represents the confusion matrix with and without a helmet, and Figure 8 represents the confusion matrix with and without seat belts. Here, the models were integrated into one framework, which clearly manifests the scalability and flexibility of the proposed system. Any changes or improvements made to any of the models will not affect the other models, thus ensuring continuous improvement to the system without any interruptions.

Dynamic adaptability to changing traffic scenarios and environments will surely enhance the utility of the proposed system as an enforcer of road safety. The real-time feedback will surely immediately notify the authorities of any violation, thus taking action with much less requirement for such activities.

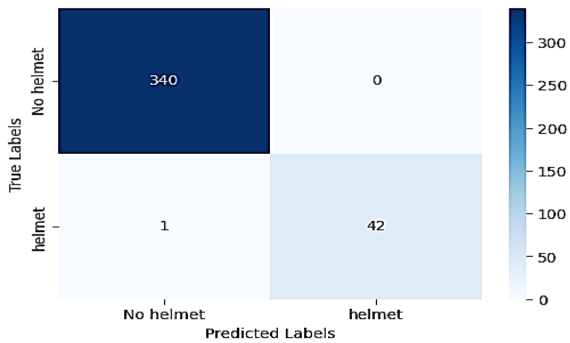

Fig. 7: Confusion matrix representing classification accuracy for the helmet detection model

Source: created by the authors

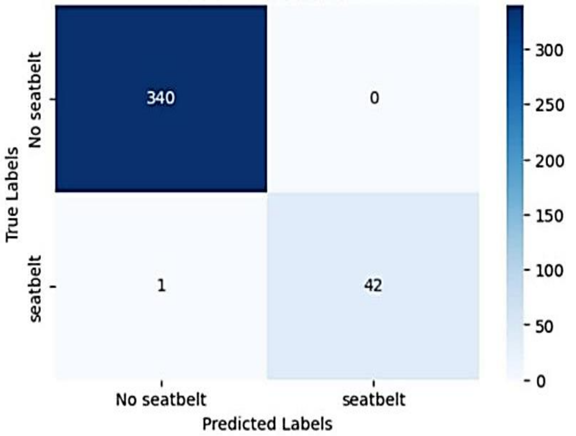

Fig. 8: Confusion matrix representing classification accuracy for the seat-belt detection model
Source: created by the authors

4.6 Error Analysis and False Detection Rates

It is important to note that the comparative models listed in Table 2 were selected to represent well-established, task-specific architectures reported in the literature for individual traffic compliance detection tasks, rather than the latest end-to-end object detection frameworks. The purpose of this comparison is not to outperform the most recent YOLO variants on isolated detection accuracy, but to demonstrate that the proposed system achieves competitive performance across multiple safety domains simultaneously within a unified, modular framework suitable for real-time deployment. This references the approach of high-performance reports only for single tasks such as face mask detection (up to 99%), lane detection (95.66%), helmet detection (91.56%), or seat belt detection (88.46%) without addressing integrated, multi-compliance enforcement.

The elevated false negative rates observed under moderate lighting conditions, particularly the 20.93% miss rate for seat belt detection, are primarily attributable to factors such as limited dynamic range, motion blur, and chromatic similarity between seat belts.

Table 2. Comparison between state-of-the-art models and the proposed model for lane detection

Model	Helmet	Seat Belt	Lane	Face Mask
CNN-based lane detection [13]	--	--	95%	--
Proposed model	**94%**	**92%**	**90%**	**95%**

Source: created by the authors

Although low-light performance is limited by current RGB sensors, future iterations can seamlessly integrate IR sensors without retraining the core CNNs, thanks to the modular architecture. These sensing limitations lessen edge contrast in low-light conditions and are not a sign of training flaws or model instability. Instead of altering the suggested CNN framework's architecture, future deployments might lessen this restriction by using better imaging hardware (such as dynamic-range or infrared-assisted cameras).

Standard definitions of accuracy, false positive rate, and false negative rate were used to derive the error metrics in Table 3 from confusion matrices. Reduced visibility, motion blur, and partial occlusions, which increase false negatives, are the main causes of performance degradation under moderate lighting conditions. To simulate real-world low-light situations, controlled illumination degradation was used to assess moderate lighting conditions. The multi-model framework shows resilience for real-time road safety monitoring at acceptable accuracy levels despite these difficulties.

Table 3. Performance (in %) under good and moderate lighting conditions

Task	Light Condition	Accuracy	False Positive	False Negative
Helmet	Good	99.73	0.2	2.33
Helmet	Moderate	96.08	2.35	16.28
Seat belt	Good	99.74	0.56	2.38
Seat belt	Moderate	95.04	2.94	20.93
Mask	Good	95	0.68	0.92
Mask	Moderate	89	2.76	12.35

Source: created by the authors

5 Insights and Implications

The experiment confirmed that CNNs were very successful at monitoring road safety compliance in real time and had good accuracy across safety parameters. Even though every model worked well, there were some situations where accuracy decreased, like when it came to recognizing helmets in low light and seat belts because of partial occlusion. These areas may be improved using sophisticated preprocessing techniques to avoid these challenges and enhance robustness. Unlike single model-based methods, this framework for integrating multiple models will reduce the computational burden on individual components while ensuring comprehensive safety coverage. The framework includes safety compliance checks for different classes in one system and refers to high-risk or high-traffic areas. As a result, it is a comprehensive and efficient method of keeping an eye on traffic safety that benefits the community.

Later models of the system can also include other elements of compliance, like object detection, vehicle speed detection, and possibly license plate detection. The system would benefit from the addition of adaptive learning capabilities made possible by AI technology, enabling the system to learn from what it has discovered from experience with real-world data inputs. Taken together, all the variables at play, the multi-model system for enhanced road safety would decrease road violations and promote responsible driving practice.

6 Conclusion

The multi-model solution for increased road safety offers a collective framework for monitoring vital factors for road compliances like helmet wear, seat belts, lane discipline, and face masks, through a composite CNN model. Although there are issues associated with light intensity detection in low illumination environments as well as occlusions, there is great scalability associated with the proposed model, with an average value of 92.75%, making a reliable starting point for automated future models for road management. Low illumination detection is still a weakness associated with RGB models, in any case, nevertheless, it is a very integrative solution for road management with great potential to make a huge impact on road compliance.

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Conflict of Interest

The authors have no conflicts of interest to declare.