A Novel Methodology to Ensure Rider Safety Measures Based on Helmet Detection System Using Deep Learning Mechanism

Gokulkannan M., Elandhiraiyan K., Gokulraj G. and Thirunavukkarasu G.

Department of Computer Science and Engineering, Mahendra Engineering College, Namakkal, Tamil Nadu, India

Keywords: Rider Safety, Helmet Detection, Image Processing, Deep Learning, EYOLO, Convolutional Neural Network, CNN, Driver Safety.

Abstract: Motorbikes are a prevalent mode of conveyance in numerous countries. Nevertheless, the absence of the appropriate safety apparatus poses a significant danger when operating a motorcycle. Consequently, it is strongly advised that individuals don helmets while operating a bicycle to ensure their safety. In order to eliminate this manual dependence, it is imperative to develop a self-powered helmet detection system that can identify motorcycle offenders. This research is dedicated to the development of a helmet detection system for two-wheelers that is both reliable and efficient. The Enhanced You Only Look Once (EYOLO) algorithm is employed in this system and it is cross-validated with the traditional deep learning algorithm, Convolutional Neural Network (CNN), to assess the effectiveness of the proposed model. The headgear status of the rider is continually monitored by this system, which operates in real-time. It rapidly determines whether the motorcyclist is donning a helmet by utilizing sophisticated artificial intelligence techniques. The primary goal of this system is to ensure that riders adhere to helmet regulations in order to enhance their safety. The system automatically precludes the vehicle from commencing in cases where the rider is not wearing a helmet, thereby encouraging the use of helmets. This proactive approach is designed to substantially reduce the risk of head injuries in the event of incidents, thereby contributing to the overall safety of the road as well as decreasing the severity of prospective injuries. Our system endeavors to improve passenger safety and reduce the negative repercussions of noncompliance with helmet regulations by combining state-of-the-art technology with regulatory compliance.

1 INTRODUCTION

Today, traffic accidents involving scooters and motorbikes are surprisingly widespread, making the safety of passengers on two-wheelers an urgent issue Gopinath D, et al., 2024. In order to tackle this pressing problem, our research utilizes artificial intelligence to identify helmet wear in real-time. Our objective is to utilize state-of-the-art technologies in a proactive manner to improve rider safety and decrease the number of serious injuries caused by accidents. The incidents are that cases of two-wheeler accidents are greatly on the rise, and the riders necessitate wearing a helmet. However, still a good number of motorcyclists prefer riding without such basic safety features, knowing very well that it is important. This system aims to develop and implement a helmet-detecting system in real-time to back up helmet regulation enforcement and accident prevention (Xuejun Jia, et al., 2020). Project objectives include enhancing rider safety and addressing environmental problems related to road accidents. Efforts are being made to lessen the toll that road accidents take on the environment by increasing safety measures and decreasing the severity of injuries through prompt medical attention. Furthermore, we aim to promote helmet usage by taking proactive steps like not allowing the vehicle to start without a helmet. This will help establish a safety culture among riders and promote a more sustainable way of getting about. With this system in place, not only would individual riders reap many benefits, but healthcare systems already overburdened by injuries sustained in accidents may also see substantial relief. We encourage sustainable mobility behaviors and contribute to society's well-being by minimizing the frequency and severity of injuries occurring from two-wheeler accidents. We want to build healthier communities and safer roads

M., G., K., E., G., G. and G., T.
A Novel Methodology to Ensure Rider Safety Measures Based on Helmet Detection System Using Deep Learning Mechanism.
DOI: 10.5220/0013869100004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 1*, pages 552-561
ISBN: 978-989-758-777-1

for everyone via teamwork and new ideas, such as the real-time helmet detection system (Hanhe Lin, et al., 2020). The following figure 1 shows the image processing block diagram.

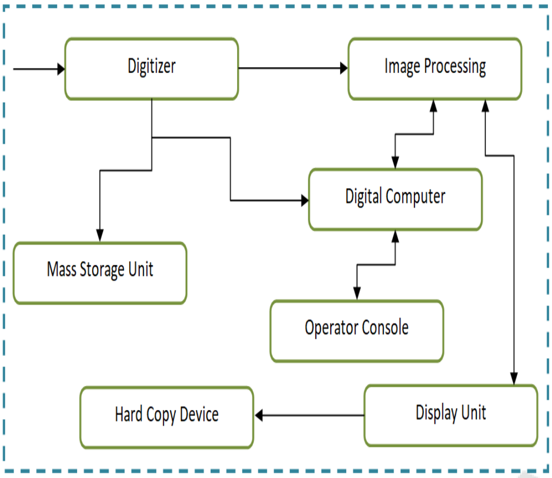

Figure 1: Image processing block diagram.

A digital image is a two-dimensional picture that has been processed by a digital computer. Any two-dimensional data may be digitally processed in a larger sense. In digital storage, each bit represents an integer array that can be either real or complex. The initial step in digitizing and storing an image in computer memory is to convert it from a digital format, such as a transparency, slide, picture, or X-ray. Digitizing the image allows for high-quality processing and/or display on a (TVYongze Ji, et al., 2022). A rapid-access buffer memory stores the image for display, and it refreshes the monitor at 25 frames per second to provide an optically continuous display (Bingyan Lin 2024). A digitizer is a machine that takes an image and turns it into a numerical form that a digital computer can understand. A few popular digital converters include

- Microdensitometer
- Flying spot scanner
- Image dissector
- Videocon camera
- Photosensitive solid- state arrays.

(Wei Jia, et al., 2021) Once an image has been acquired, stored, preprocessed, segmented, represented, recognized, and interpreted, finally, this image could be displayed or recorded by an image processor. The image sensor and digitizer work together in capturing an image, which is the first stage in the process (M. Saravanan, et al., 2024) The next stage is the preprocessing stage, where the image is enhanced for subsequent operations. Enhancement, noise removal, area isolation, etc. are common topics in preprocessing. An image can be "segmented" into its individual elements by using this technique. Raw pixel data, including either the region's border or the pixels inside the region, is often what comes out during segmentation. To prepare the raw pixel data for further processing by the computer, a procedure known as representation must be carried out. The primary focus of description is the extraction of characteristics that serve as fundamental differentiators between various object classes. Based on the data supplied by the object's descriptors, recognition provides it a label. The process of interpretation entails giving significance to a set of identified items. The knowledge base is enriched with knowledge acquired from the knowledge body relevant to the problem domain. (Sheela S Maharajpet, et al., 2024). The knowledge base further governs the inner workings of the processing modules and their interactions among themselves. Not all modules need to be in place to do a particular job. The application specifies the composition of the image processing system. Typically, the image processor's frame rates are around 25 fps (Maros Jakubec, et al., 2023).

(i) Digital Computer: On the digital image, the computer applies mathematical operations including adding, subtracting, averaging, and convolution.

(ii) Mass Storage: Auxiliary storage devices like as floppy discs and CD ROMs are widely used.

(iii) Hard Copy Device: This device stores the relevant software and creates a permanent copy of the picture.

(iv) Operator Console: In order to make software adjustments or verify intermediate results, the operator console has the necessary tools and configurations. Moreover, the operator may validate the entering of all necessary data and any errors that may have arisen in consequence.

Digital image processing is when image data is processed supported by some digital means. Images originate most of the time in an optical way; the modern state of the cameras just takes images massively in digital form. The other option is to video-capture them and converts to the digital form. During the digitization process, sampling and quantization are performed. These images would normally be processed by one or more of the five basic operations (Chentao Shen, et al., 2023). Several methods for processing images are detailed in this section.

(i) Image Enhancement: Operations that increase a image quality, such as enhancing its contrast and brightness, decreasing its noise content, or sharpening its features, are known as image enhancement. This only improves the image by making it more comprehensible while still revealing the same information. It doesn't enrich it with any new details.

(ii) Restoring Images: Just like image enhancement, image restoration works to restore a image quality, but it relies heavily on measurements or known degradations to do so. Geometric distortion, out-of-focus areas, repeated noise, and camera shake are all examples of image restoration issues. Images have the means for the correction of known degradations.

(iii) Analyzing Images: Operations in image analysis can turn attributes of the original image into either numerical or graphical data. Dismantle them to put them in categories. The statistics of the images will govern their use. Common tasks include object categorization, automated measurement, scene and image feature extraction and description, and automated measurement. The majority of image analyzers' usage is in machine vision tasks.

(iv) Image Compression: Compressing and decompressing images lessens the amount of data needed to describe a image. Compressing photos gets rid of all the unnecessary data that is often included in them. The size is lowered by compression, making it ideal for convenient storage or transportation. Decompression occurs when seeing the image. Lossy compression enhances compression at the expense of the original picture, in contrast to lossless compression, which preserves all of the original image's data.

(v) Image Synthesis: Operations in image synthesis generate new images from existing ones or from data that does not contain images at all. In most cases, image synthesis techniques produce results that would be extremely difficult.

Several methods of image encoding are detailed below.

- A binary image, in which each pixel is either black or white. We just require one bitper pixel since each pixel may take on one of two potential values (0 or 1).
- A grayscale image typically uses a range of grayscale values, from 0 (black) to 255 (white), for each pixel. Because of this range, a single byte—eight bits can represent each pixel. In most cases, grayscale values are a power of 2, however, other values are utilized.
- A color map matrix plus an array makes up an indexed image. In this array, each pixel value is an index into a color map. The array is denoted by the variable name X in this text, whereas the color map is referred to as map.
- A RGB image, often known as a true color image, is one in which the relative amounts of red, green, and blue give rise to distinct colors for each pixel. There would be 2563 distinct color combinations if the values of these variables could vary from 0 to 255. A "stack" of three matrices, one for each pixel's red, green, and blue values, constitutes such an image. So, there are three values that correspond to each pixel.

2 RELATED WORKS

Motorbike use as a mode of transportation is a common practice in many countries. However, the absence of certain protective gear while riding poses a threat to a rider (Rupesh Chandrakant Jaiswal, et al., 2022). Therefore, wearing a helmet is very necessary for your safety while riding. Therefore, it is cardinal to build such a system to identify motorcycle helmets and criminals in order to eliminate this dependence on the human inspectors. Some biker riders don't see the need to wear a helmet, but some only do when they see a traffic cop. This project endeavors to design an autonomous system functional in real-time, with a focus on the YOLO deep learning approach. The YOLO CNN is trademarked for real-time object detection.

Safety helmets are essential in many outdoor and indoor industrial settings, including high-temperature metallurgical activities and the construction of towering buildings (Qing An, et al., 2023). Nevertheless, human error and a lack of compliance are common problems with manual monitoring, which also adds to its high cost. In addition, accuracy is often lacking while detecting tiny target objects. A potential solution to these problems is to enhance safety helmets using the helmet detection algorithm. Lightweight deep learning object identification model YOLOv5s was updated and showcased in this study. Recalculating the prediction frames, clustering using the IoU metric, and altering the anchor frames using the K-means++ approach improve the performance of the suggested model, which is an extension of the YOLOv5s network model. In order to strengthen the YOLOv5s network's backbone and neck networks, a mix of the global attention mechanism and the convolutional block attention module was utilized. Deep learning neural networks are able to extract more features thanks to these attention techniques, which enhance the representation of global interactions and minimize the loss of information characteristics. Improving target feature extraction and reducing computation required for model operation are both achieved by the inclusion of the CBAM into the CSP module. The suggested model employs the most current SIoU (SCYLLA-IoU LOSS) as the boundary box loss function to enhance the prediction box regression. A lightweight network model that meets the demands of real-time monitoring is constructed on top of the upgraded YOLOv5s model. Knowledge distillation technology reduces the model's computational effort while enhancing detection speed. All three metrics—precision, recall, and mean average precision—show that the suggested model beats the prior YOLOv5s network model in experimental results. Even in dim light and from varying distances, the suggested model might be able to better detect helmet wear.

The workplace must be visually inspected and immediately inform the workers when they do not wear a safety helmet so that injuries on the job could be avoided (Yange Li, et al., 2020). For that matter, a need arises for automatic real-time detection from the great amounts of unstructured visual data created by on-site video monitoring systems. Despite the abundance of research on deep learning-based helmet detection models for traffic surveillance, there has been surprisingly little discussion of a suitable solution for industrial use, especially when considering the complexity of the environment on a construction site. To that end, we create a system that uses deep learning to identify safety helmets on the job site in real time. This approach makes use of the convolutional neural network-based SSD-MobileNet algorithm. A public dataset with 3,261 photos of safety helmets was created and made available to the public. The photographs came from two sources: the workplace's video surveillance system and open images retrieved with web crawler technology. The picture set is sampled in a manner that is about 8:1:1, with each set serving as a training set, validation set, and test set. Using the SSD-MobileNet method, the experimental findings show that the given deep learning-based model can efficiently and accurately detect risky operations including the failure to wear a helmet on a construction site.

A comprehensive system of safety management has been built up by power grid enterprises within China to regulate restrictions, such as all safety rules and two tickets embodied into one, for the assurance of the operation's stability and protection of staff (Songbo Chen, et al., 2020). On the other hand, a good number of workers still show lack of safety consciousness by not wearing helmets in their jobs inside substations. Electric power workers must always wear safety helmets to protect their heads from potentially lethal accidents including electric shock and strikes. Not only does working without a helmet contradict the safety control system; it depicts one as careless with the lives and possessions of people. However, these controlling measures currently are not efficient, effective, and quick enough to detect and prevent such acts. This research suggests using the Improved Faster R-CNN algorithm to check if a person is wearing a safety helmet so that we may better prevent this dangerous behavior. Taking into account the actual circumstances, the Retinex image improvement is implemented to increase the quality of images captured in substations of outside complex situations. Additionally, the K-means++ technique is utilized to enhance the helmet's adaptability to its little size. The findings of the experiments demonstrate that the Improved Faster R-CNN algorithm achieves better mean-average precision than the Faster R-CNN method, allowing for the automated identification of safety helmet wears in real-time.

The construction industry is still sky-high in its expansion, hence new and unique dangers to workers' health and safety arise out of active construction. Wearing helmets while on a construction site can greatly lower the chance of incurring an injury (Lihong Wei, et al., 2024). Hence, the objective of this research is to propose a deep learning approach in real-time for detecting whether construction workers are using helmets or not. This study examines the training outcomes of the YOLOv5s network that was chosen through trials. Given that it has a weak ability to identify tiny items and objects that are partially obscured. This leads to a number of improvements to the YOLOv5s network, a change to the feature pyramid network to a BiFPN bidirectional feature pyramid network, and an upgrade to Soft-NMS from NMS, the post-processing methodology. The loss function is optimized hereby enhancing the convergence and detection speed of the model, which introduces BiFEL-yolov5s: A YOLO V5 series model enhanced by a combination of BiFPN networks and Focal-EIoU Loss. The model's average accuracy is improved by 0.9%, its recall rate is enhanced by 2.8%, and its detection speed is kept relatively constant. It meets the needs of helmet detection in a variety of work situations and is thus more suitable to real-time safety helmet object detection.

3 METHODOLOGY

A wide range of scientific and technological disciplines can benefit from image processing techniques. Some examples of the many uses for image processing are presented in this brief list.

(i) Processing Documents: scanning and transmitting them involves processing the documents, which involves transforming them into digital images, compressing them, and then storing them on magnetic tape. It also has additional applications in document reading, such as automatic feature detection and recognition.

(ii) Health Care: examining and interpreting X-ray, magnetic resonance imaging (MRI), computed tomography (CT) pictures, images of individual cells, and chromosomal karyotypes. The processing of medical images from radiology, nuclear magnetic resonance (NMR), and ultrasonic scanning, including chest X-rays, cineangiograms, and projection pictures of transaxial tomography, is one area of interest in medical applications. These images may find value in cancer and other illness screenings, patient monitoring, and diagnosis.

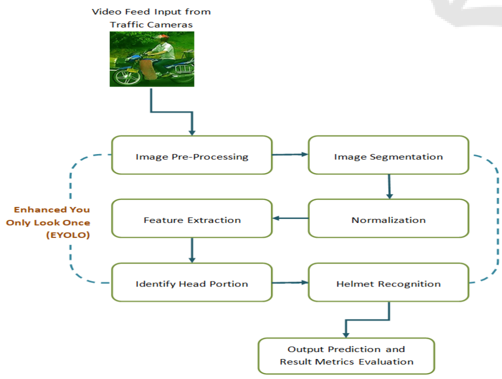

Figure 2: Proposed block diagram.

(iii) **Industry:** Paper sample inspection, automated checking of manufacturing line items.

(iv) **Defense/Intelligence:** Applications include reconnaissance photo-interpretation, which uses automated analysis of Earth satellite imagery to seek for sensitive targets or military threats, and target acquisition and guidance, which aids in the identification and tracking of targets in real-time smart-bomb and missile-guidance systems.

(v) **Radar Imaging System:** Aircraft and missile systems obtain their guiding and maneuvering information from radar and sonar images, which are utilized for target identification and recognition.

(vi) **Agriculture:** Satellite and aerial images of land may be utilized for a variety of reasons, such as measuring land usage, researching which places are most suited for certain crops, and inspecting product to determine if it is fresh or old.

3.1 Video Feed from Camera

The camera on-board to record all activities of a two-wheeler rider is the most vital technology for helmet recognition. The camera stands right at the forefront of sensory input for the AI system by providing live visual information about the activities of the rider and the environment around them. As a streaming device, the camera allows live monitoring of the rider for any possible helmet compliance violation. The camera captures the activities and motions of the rider to determine whether the person is wearing a helmet or not. Information that a live video stream provides would give the system enough room to spring into action anytime the rider is not wearing a helmet. With this contextual information, such as traffic and road barriers from the camera, the overall safety of the rider can be assessed in a more effective manner. This function of capturing live video input is an important aspect of the helmet detection system, which is designed to take proactive measures toward enhancing rider safety in two-wheelers. Figure 2 shows the Proposed Block Diagram.

3.2 Capture the Image

The two-wheeler helmet recognition system relies on the following steps: the capturing of images that will mostly contain everything required by the recognition analysis. The images are basically frames extracted from the real-time video stream captured from the camera. An image therefore, is like a snapshot during a period in time, the raw material that makes up every processing and analysis that will go on afterward. The system is that it enables continuous data feed for helmet detection whereby frames are taken at regular intervals to allow for real-time checks on the state of the rider's helmet. It, therefore, assists better in the efficient utilization of computing resources and speedy decisions on the wearing of helmets. This step thus becomes the important component in detecting the helmet and enables the system to determine the rider's actions while taking requisite measures toward the safety security of two-wheelers.

3.3 Preprocessing

The two-wheeler helmet identification system relies heavily on preprocessing to get the recorded images ready for analysis. Several preprocessing processes are performed on the collected frames from the live video feed to improve their quality and make them more suitable for further analysis. Since various images need to be processed fast and with lower computational complexity, it is predetermined that their sizes must be equal. There are various normalization techniques which can standardize the pixel values to allow for better comparison and study of different images. Other noise filtering methods such as median filtering and Gaussian blurring can really help in reducing interference caused by noise and beautifying the image quite nice. After these preprocessing techniques, which enhance the obtained photographs for accurate helmet detection, the system can safely and rightly evaluate the rider's helmet standing and therefore take measures to provide safety on two-wheelers.

3.4 Feature Extraction

The important thing in helmet identification system of two-wheelers is feature extraction, which punctuates absorbing knowledge from the pre-processed images whereby they will tell the system if the rider is armed with a helmet. Important features extracted from the pre-processed images may include color, shape, and texture. While shape features detail the external outline and structure of possible helmets in the image, color features captured assist in analyzing the patterned colors of helmets. Anyway, texture features sometimes help distinguish helmets from other items or backgrounds in the picture by serving as a clue to some properties of the surface of these items. Thus, the feature extraction process serves to strengthen the information providing a clearer picture of the shots enabling the system to distinguish between helmet on or off instances. This will allow the system to check when the rider is wearing a helmet and then take measures concerning perhaps a safety crackdown concerning two-wheelers.

3.5 Database Collection

A reliable AI model built on the two-wheeler helmet recognition system relies on database collection. The first step is to prepare a large dataset of labeled images containing both helmeted and helmetless bikers. Each image in the collection is doted by well-defined annotation to indicate the presence of a helmet or not. The deep learning algorithm is then trained over the labeled dataset, which is intended to convey the model to find features relating to helmet identification. The dataset, when used to train the model, allows the model to generalize better on unseen data by showing the examples of various conditions under which the helmets are worn and non-worn. Creating a strong and dependable two-wheeler helmet detection system would depend on database collecting.

3.6 Training

The phase during which identification of helmets on two-wheeled vehicles is being undertaken is the training one, which must be handled with extreme care since it's here where the AI model gets to learn to differentiate among different types of helmets through observing patterns from a labeled dataset. The training is generally performed using deep learning algorithms like YOLO, which means "You Only Look Once." In training, the model gets its internal parameters tuned, i.e., reduces the difference in predictions and actual ground truth labels, by iteratively iterating over the labeled dataset. The model learns how to identify helmets distinguishing images of people wearing helmets from the images of people not wearing helmets by modifying its parameters repeatedly through backpropagation. The model's training is aimed toward making it the best in detecting helmets in varied environments, illumination, and orientation and background. The model's training helps it to be good at detecting helmets on live video feeds, improving the safety of motorcyclists.

3.7 Testing

In the two-wheeler helmet recognition system, testing holds great importance. It is used to assess both the efficacy of the training techniques and how well the trained model may generalize. After having trained itself on the labeled data sets, the model is evaluated with another new set of test images, unseen previously. The test images incorporated some real-life scenes such as varying lighting, different rider positions, or many backgrounds. Each test picture will be analyzed by the model for the presence of helmets and outputs are made based on the analyses. The predictions made by the model are then compared to the ground truth labels in order to assess model performance, i.e., accuracy, precision, recall, and so forth. Testing on unseen data is important for assessing a model's generalizability along with its potential for high accuracy in helmet detection in various real-life situations. This step is critical to ensuring that the helmet detection system is both reliable and effective in enhancing the rider's safety while riding two-wheelers.

3.8 Identified Helmet Wear (or) Helmet not Wear

In each frame of the live video feed in real-time, the model trained on helmet detection infers decision from past data as whether a helmet is in use or not. Based on criteria set for attributes learned during training, this once again assures, based on one frame, the model decides whether a biker has put on a helmet or not. This makes it possible for the vehicle to proceed if the model sees a helmet that is sufficiently confident to meet safety standards. If, however, a helmet is not seen or seen with low confidence by the model, the system would not allow the rider to move forwards on the bike until one was placed on. In doing so, the preventive measures aim at lowering the chances of head injuries during mishaps and the compulsory wearing of the helmet for rider safety. By keeping a constant check on the state of the rider's helmet in real-time, the technology establishes a culture of safety and compliance on two-wheelers.

4 RESULTS AND DISCUSSION

Using the EYOLO (Enhanced You Only Look Once) architecture, this research suggests a real-time helmet identification system that has been trained on 4,956 photographs, with 80% of the images being used for training and 20% for validation. This suggested EYOLO achieved the highest prediction accuracy of 98.84% among the numerous deep learning variations that were assessed, demonstrating exceptional performance in the identification of safety helmets, even in low-light conditions. The EYOLO model, in conjunction with learning and classification methods, was employed to identify helmet infractions among motorcyclists in this research. The model demonstrated the ability of deep learning to identify helmet rule violators in challenging illumination and weather conditions after being trained on 250 films that were captured at 25 frames per second and each lasted 25 seconds. The proposed model's potential for real-time traffic surveillance and enforcement is underscored by its high accuracy score. In general, helmet detection systems have been significantly improved by advancements in deep learning, particularly in the context of EYOLO architectures. The model that has been proposed underscores the exceptional accuracy and real-time performance of various EYOLO architectures in the detection of helmet usage, thereby promoting enhanced safety measures in traffic surveillance and construction areas. A representation of the input image for the proposed technique may be seen in the accompanying figure, which is referred to as Figure 3. This image is obtained from the video feed of traffic cameras.

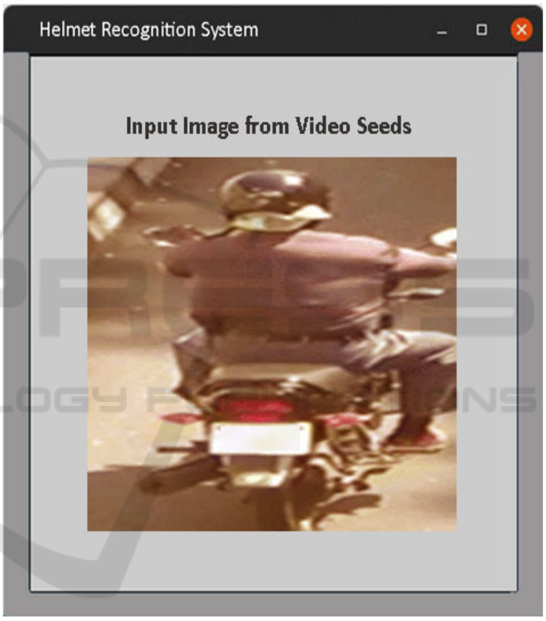

Figure 3: Input image gathered from traffic cameras video feed.

The consequences of the suggested method for picture pre-processing and segmentation are depicted in the accompanying figures, namely Figure 4 and Figure 5.

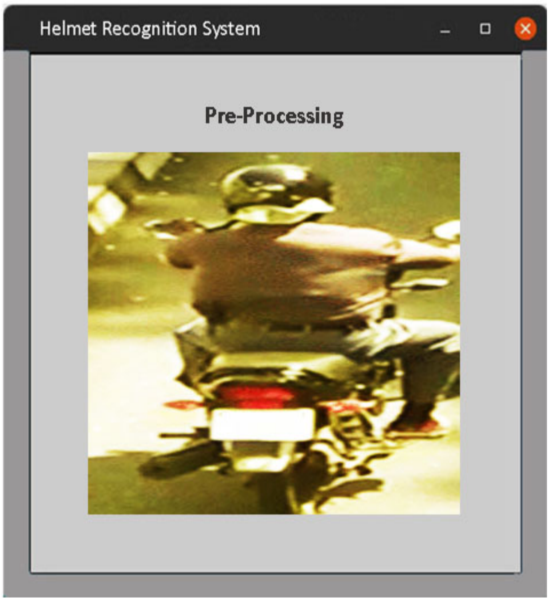

Figure 4: Image pre-processing.

Figure 5: Segmentation.

The outputs of the feature extraction and helmet identification stages of the proposed technique are depicted in the accompanying figures, namely Figure 6 and Figure 7.

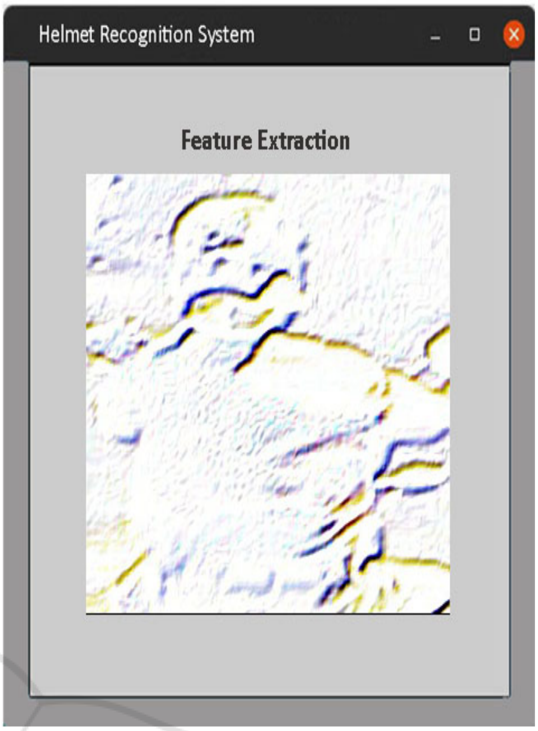

Figure 6: Feature extraction.

Figure 7: Helmet recognition.

The prediction accuracy level analysis of the proposed scheme, EYOLO, is depicted in the accompanying figure, Figure 8. This analysis is conducted by cross-validating the proposed model with the traditional learning algorithm, CNN, in order to assess its prediction accuracy. Table 1 is a descriptive representation of the aforementioned.

Table 1: Analysis of prediction accuracy between CNN and EYOLO.

Epochs	CNN (%)	EYOLO (%)
100	94.25	98.83
150	92.64	98.58
200	91.72	98.49
250	92.08	97.37
300	90.67	97.92
350	90.96	98.09
400	90.78	97.53
450	91.99	98.34
500	90.69	98.52
550	92.27	98.84
600	92.56	98.84

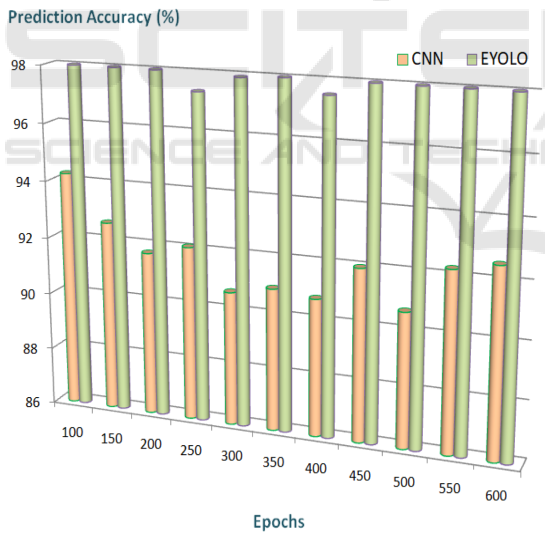

Figure 8: Prediction accuracy.

5 CONCLUSIONS

In summary, the helmet detection system for two-wheelers is a proactive measure that integrates real-time monitoring capabilities and artificial intelligence to enhance passenger safety. The system effectively determines whether motorcyclists are wearing helmets by analyzing live video transmissions, thereby facilitating the enforcement of safety regulations. The system obtains commendable accuracy in detecting helmets across diverse real-world scenarios through extensive testing, rigorous model training, and meticulous database collection. Consequently, it cultivates a culture of safety, thereby reducing the likelihood of head injuries on two-wheelers and making a substantial contribution to the safety of roads and the overall well-being of motorcyclists. In conclusion, the helmet detection system is a critical technological solution in the field of road safety, providing tangible advantages in the areas of regulatory compliance and injury prevention. Its significance in promoting safer riding practices and decreasing the incidence of head injuries is emphasized by its capacity to promptly identify non-compliance and implement enforcement measures. This system not only improves the safety of individual motorcyclists but also contributes to the overarching objective of establishing safer road environments for all road users, thereby fostering a culture of responsibility and well-being within the community, by utilizing state-of-the-art AI technologies.

This work can be improved in the future by promoting safer cycling behaviors and encouraging helmet usage by providing real-time alerts or feedback to the rider. In addition to enhancing rider safety by expanding the system to detect other safety gear or objects of interest, such as reflective clothing or road hazards, and by integrating the helmet detection system with vehicle systems to enable features such as automatic emergency braking or adaptive cruise control based on the rider's safety status.

REFERENCES

Bingyan Lin, "Safety Helmet Detection Based on Improved YOLOv8", IEEE Access, 2024.

Chentao Shen, et al., "Small-scale helmet detection based on improved YOLOv5 and moving object detection", Proceedings of the 2023 ACM Symposium on Spatial User Interaction, 2023.

Gopinath D, et al., "Detection of Helmet and License Plate Using Machine Learning", International Journal of Intelligent Systems and Applications in Engineering, 2024.

Hanhe Lin, et al., "Helmet Use Detection of Tracked Motorcycles Using CNN-Based Multi-Task Learning", IEEE Access, 2020.

Lihong Wei, et al., "Research on helmet wearing detection method based on deep learning", Scientific Reports, 2024.

M. Saravanan, et al., "Comprehensive study on the development of an automatic helmet violator detection system (AHVDS) using advanced machine learning techniques", Computers and Electrical Engineering, 2024.

Maros Jakubec, et al., "Deep Learning-Based Automatic Helmet Recognition for Two-Wheeled Road Safety", Transportation Research Procedia, 2023.

Qing An, et al., "Research on Safety Helmet Detection Algorithm Based on Improved YOLOv5s", Sensors, 2023.

Rupesh Chandrakant Jaiswal, et al., "Helmet Detection Using Machine Learning", Journal of Emerging Technologies and Innovative Research, 2022.

Sheela S Maharajpet, et al., "Advanced Safety Helmet Detection: Enhancing Industrial Site Safety with AI", QTanalytics Publication, 2024.

Songbo Chen, et al., "Detection of Safety Helmet Wearing Based on Improved Faster R-CNN", International Joint Conference on Neural Networks, 2020.

Wei Jia, et al., "Real-time automatic helmet detection of motorcyclists in urban traffic using improved YOLOv5 detector", IET Image Processing, 2021.

Xuejun Jia, et al., "High-Precision and Lightweight Model for Rapid Safety Helmet Detection", Sensors, 2024.

Yange Li, et al., "Deep Learning-Based Safety Helmet Detection in Engineering Management Based on Convolutional Neural Networks", Advances in Civil Engineering, 2020.

Yongze Ji, et al., "Research on the Application of Helmet Detection Based on YOLOv4", Journal of Computer and Communications, 2022.