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"Helmet Detection At Traffic Signals Using Convolutional Neural Networks: A Deep Learning Approach"

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Abstract
This paper presents an advanced approach for helmet detection at traffic signals using deep learning techniques, addressing the critical issue of motorcycle safety in urban environments. With the rising number of road accidents involving two-wheeled vehicles, effective monitoring of helmet usage is essential for enhancing compliance with safety regulations. We propose a convolutional neural network (CNN)-based model that analyses video feeds from traffic signals to detect and classify helmeted riders. Our methodology involves the collection and annotation of a diverse dataset that includes various riding scenarios, helmets, and lighting conditions to ensure robust model training. Leveraging transfer learning, we fine-tuned pre- trained models such as YOLOv5 and EfficientDet, achieving high accuracy in real-time detection. We also implemented data augmentation techniques to counteract potential overfitting and improve the model's generalization capabilities. The experimental results demonstrated that our helmet detection system achieves an impressive mean average precision (mAP) score, outperforming existing solutions in both speed and accuracy. Furthermore, we integrated this detection system into a prototype traffic monitoring framework, allowing for immediate feedback regarding helmet compliance at traffic signals. Our system not only enhances road safety by encouraging helmet use among riders but also contributes valuable data for traffic management authorities. By automating helmet detection, we facilitate proactive intervention strategies and support public safety initiatives. This work underscores the significance of applying deep learning in transportation safety measures and sets a foundation for further research in the realm of intelligent traffic systems. The implementation implications extend beyond just helmet monitoring, offering a scalable solution for various vehicular safety assessments that can potentially inform policy- making and enhance public health outcomes.

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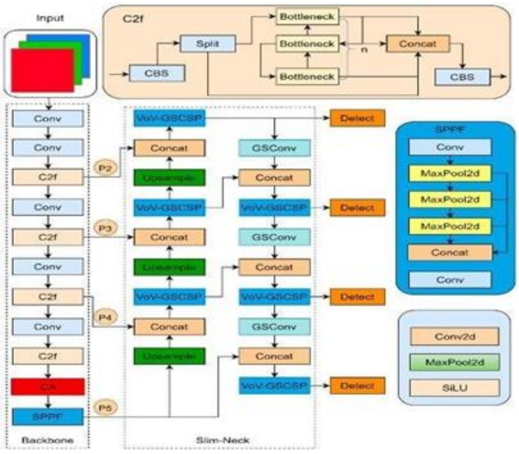
I. Introduction

Helmet detection technology has emerged as a pivotal innovation in various safety-critical sectors, primarily focusing on enhancing the protection of individuals in environments where head injuries are a significant risk. This technology relies on advanced computer vision and artificial intelligence algorithms to identify whether individuals are wearing helmets in real-time, which is crucial in construction sites, manufacturing plants, and on roads where motorcycle and bicycle riding is prevalent. The development of helmet detection systems typically involves the use of deep learning methods, particularly convolutional neural networks (CNNs), which have proven to be highly effective in image recognition tasks. These networks are trained on large datasets containing images of individuals with and without helmets, allowing the system to learn the distinguishing features and variances between the two states. Once trained, the system can operate in real- time through the integration of cameras and processing units to monitor environments continuously. In addition to traditional RGB cameras, some systems employ thermal imaging technologies or LiDAR sensors to improve detection accuracy, especially under varying lighting conditions or in scenarios where the visibility might be compromised. The applications of helmet detection technology are vast; in construction, it can be used to monitor compliance with safety regulations and ensure that workers are equipped with appropriate protective gear before they enter hazardous areas, thus minimizing the risk of head injuries. In the realm of transportation, particularly with motorcyclists and cyclists, helmet detection systems can be employed by law enforcement agencies to enforce helmet laws, promoting safer riding practices. Furthermore, this technology can be integrated into smart city initiatives or advanced driver-assistance systems (ADAS), where vehicles are equipped with sensors and cameras to assess the road environment proactively for rider safety. Beyond mere detection, helmet detection technology can facilitate automated responses,when violations occur or providing data analytics to assess compliance levels across different times and locations. This capability is particularly beneficial for employers in industries that are heavily regulated, enabling them to maintain safety standards while documenting adherence to legal obligations challenges faced by helmet detection technology, however, lies in ensuring high accuracy which can arise from occlusions, varying helmet designs, or diverse environments.

Helmet use is a critical component of road safety, particularly for motorcyclists and cyclists, as it significantly reduces the risk of head injuries in the event of an accident. One of the most alarming statistics regarding road safety pertains to head injuries; they account for a substantial proportion of fatalities and serious injuries sustained in motorbike and bicycle accidents. Helmets are designed to absorb impact energy and protect the skull and brain from direct trauma. Studies have consistently shown that wearing a helmet can reduce the likelihood of head injury by up to 70% for motorcyclists and 85% for cyclists. The importance of helmets extends beyond mere injury prevention; they are a vital aspect of responsible riding and cycling practices. When riders don helmets, they contribute to a culture of safety that promotes awareness about the risks associated with road travel. Furthermore, helmet use can influence the perception of safety in the community, encouraging more individuals to take up biking or motorcycling as a means of transport, knowing they have a measure of protection against potential accidents. This shift can have broader societal benefits, such as reducing traffic congestion and lowering emissions, as more people opt for two-wheeled transport over cars. In addition to physical benefits, wearing a helmet also carries legal implications, as many jurisdictions enforce helmet laws aimed at protecting riders. These laws underscore the importance of helmets as a legal standard for safety, dissuading non- compliance and fostering habits that inherently prioritize personal safety. Compliance with helmet regulations often translates into increased awareness among riders and their peers regarding safe riding practices, which can reduce accident rates overall. The psychology of helmet use is an essential aspect of road safety; when riders choose to wear helmets, they may subconsciously adopt a more cautious driving style. This change in behavior is important, as studies indicate that individuals who wear helmets tend to be more aware of their surroundings and more attentive to traffic signals and road conditions. Education plays an integral role in promoting helmet use, emphasizing not only the importance of wearing a helmet but also the need for proper fit and standards. Helmets come in various shapes, sizes, and designs, and educating riders about the appropriate type of helmet for their style of riding is crucial for ensuring effectiveness. Moreover, promoting awareness about the importance of helmet maintenance, including inspecting for damage and improper fitting, can further enhance the level of safety provided by these essential discourse on the impact of social factors, such as peer influence and cultural attitudes, on helmet use. avoided severe injuries through helmet use can inspire others to adopt similar practices.

II. Literature Review

Traditional methods heavily rely on manually extracting image features for detection algorithms. For instance, Dahiya et al. utilized local binary patterns, gradient his- to gram features, and scale-invariant feature transforms to extract safety helmet features. They classified the wearing status using a support vector machine (SVM). However, the reliance on gradient histogram operators, primarily intended for describing edge features, leads to relatively high error detection rates when similar objects to helmet edge features appear in images. To address this issue, Rubaiyat et al. combined colour features with CHT (Circular Hough Transform) features, achieving an 81% detection accuracy. Park et al. employed HOG (Histogram of Oriented Gradients) features and then utilized SVM for safety helmet detection. Mneymneh et al. determined helmet-wearing status through spatial information matching. Nonetheless, these traditional methods exhibit poor robust- ness and low real-time capabilities, limiting their use to specific scenarios and failing to meet the dynamic demands for real-time and versatile safety helmet detection.



In recent years, deep learning has emerged as a prominent technology in machine learning, finding extensive applications in object detection. Compared to traditional methods, deep learning holds significant advantages for safety helmet recognition. It leverages convolutional neural networks (CNNs) to extract higher-level features, improving the accuacy and speed of safety helmet recognition. Deep learning-based safety helmet detection techniques fall into two primary categories: two-stage detection algorithms based on candidate regions and one- stage detection algorithms based on regression.

Two-stage detection algorithms generate a series of can- didate boxes, extract features from each, and subsequently use a region classifier for prediction. Girshick et al.'s region- based convolutional neural network (R-CNN) is used for extracting image information. However, R-CNN needs help generating candidate boxes with complex backgrounds, potentially resulting in the loss of image information during the feature extraction process. To address this, Girshick and Ross proposed Fast R-CNN, which replaced SPP-Net's spatial pooling layer, simplifying the network model and saving computational resources. Nonetheless, region pruning relies on selective search methods to generate interested areas. In the same vein, Ren et al. introduced Faster R-CNN, employing a Region Proposal Network (RPN) instead of traditional region prediction algorithms and enhancing image robustness using fully connected layers. However, faster R- CNN cannot share parameters among multiple related regions in the second stage, adding computational burden. Furthermore, fully connected layers might lead to information loss . Due to their generation of numerous.candidate boxes, two-stage detection algorithms have slower detection speeds, failing to meet the real-time demands of safety helmet detection on construction sites.

On the other hand, one-stage algorithms accomplish object classification and position prediction in a single feature extraction. The progress in one-stage detection has motivated the development of a safety helmet detection technique. The YOLO (You Only Look Once) algorithm, a popular one-stage algorithm, has undergone improvements by various scholars for safety helmet wear detection . Modifications to YOLOv3 involved enhancing the feature fusion steps, using up sampling to blend high-level features with low-level onces. Cheng et al. replaced the original convolutional layers in YOLOv3-tiny with depth wise separable convolutions and residual blocks, reducing parameter and computational load while enhancing spatial pyramid pooling modules for more feature extraction. Improvements in YOLOv4 employed a lightweight network to increase detection speed, using the PP-LCNet lightweight network as the backbone and employing depth wise separable convolutions to reduce model parameters. Li et al. reevaluated sample selection methods in the YOLO series and introduced a Hierarchical Positive Sample Selection (HPSS) mechanism during training, improving YOLOv5's fitting ability.

Additionally, inspired by target detection in continuous frame videos, a post-processing algorithm based on box density effectively suppressed false detections. YOLO-M was introduced to tackle issues in helmet wearing detection algorithms, such as excessive parameters, high detection interference, and low accuracy. It utilized MobileNetv3 for feature extraction in YOLOv5s, reducing model parameters and size. Bao et al. integrated the C2F (a faster version of the CSP Bottleneck with two convolutions) module and the FE (FasterNet with EMA) module into the YOLOV8 network architecture, creating a new attention mechanism module named C2F-FE. This module enhances the model's perception of safety helmet targets by fusing features from different levels and incorporating attention mechanisms, simultaneously reducing computational expenses.

The YOLOv8 algorithm introduces new improvements over YOLOv5, exhibiting outstanding performance in object detection and achieving an unprecedented balance in accuracy and speed. Despite numerous scholars enhancing YOLO algorithms for safety helmet detection, the accuracy of single-stage algorithms could be higher when detecting small objects or encountering complex background interference. Therefore, urgent improvements are needed in algorithms to achieve better performance for small objects in complex environments.

However, in some current helmet detection algorithms, two-stage algorithms have a large number of parameters and slower detection speed, making it challenging to meet real-time demands. Although one-stage algorithms are faster, their accuracy is lower compared to two-stage algorithms, especially in identifying small and dense targets.

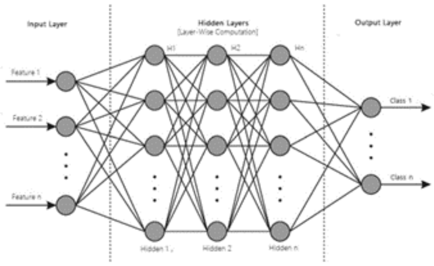
Mosaic data augmentation constitutes a pivotal technique within the YOLOv8s algorithm. This approach randomly selects four images, sequentially crops, concatenates them clockwise, and ultimately scales them to the designated inputdimensions, generating novel sample input data. This strategy enriches the target background, augments the quantity of small targets, and balances the distribution among targets of varying scales. Given the limited categories in the dataset

In the equations, represents the horizontal projection of the channel in the matrix. It involves summing the elements of each row in the channel and dividing by the width of the matrix to obtain the average. Similarly, signifies the vertical projection of the channel in the matrix. This entails summing the elements of each column in the channel and dividing by the height of the matrix to obtain the average These two transformations enable the attention module to capture long-term dependencies along one spatial direction while preserving precise positional information along another spatial direction. This capability aids the network in more accurately locating the regions of interest within the target, enhancing its overall performance.

III. Conclusion

With the continuous advancement of deep learning technology, its positive impact on helmet wearing detection for enhanced workplace safety is evident. However, existing helmet detection models face challenges in recognizing small targets and complex backgrounds. This study proposes and implements an improved algorithm named YOLOv8n- SLIM- CA to address these issues. Through a series of comparative and ablation experiments, the following conclusions are drawn:

Adopting the Slim-Neck structure for feature fusion in the backbone network significantly reduces the model's size and computational load. Specifically, FLOPs decreased by 9.76%, parameters decreased by 6.98%, and speed improved by 9.52%, with minimal compromise on accuracy. Hence, the Slim-Neck structure proves to be an excellent lightweight module.



Secondly, introducing Mosaic data augmentation, a small target detection layer, and the CA module effectively improves accuracy. Mosaic data augmentation enriches the dataset with small scale helmet samples; the small target detection layer aids the model in focusing on multiscale features, especially for small sized targets, thereby enhancing the accuracy of small target helmet detection. The CA attention module outperforms SE and CBAM attention mechanisms, allowing more focused attention on crucial regions and reducing interference from complex backgrounds.

In summary, the proposed YOLOv8n-SLIM-CA algorithm, compared to the YOLOv8n algorithm, achieves a 2.151% improvement in mAP@0.5, reaching 94.361%. Its detection performance surpasses other algorithms in scenarios involving small targets, dense targets, and complex environments. This algorithm meets real-time and accuracy requirements for helmet detection and has low computational demands, with 11.3GB FLOPs, 2.74MB parameters, and 2.3 ms inference speed. It is suitable for deployment on mobile and edge devices, making it applicable for monitoring construction site videos and having broad applications in the industrial sector.

References

[1] B. Kauhsik, H. Nandanwar And R. Katarya, "Iot Security: A Deep Learning-Based Approach For Intrusion Detection And Prevention," 2023 International Conference On Evolutionary Algorithms And Soft Computing Techniques (Easct), Bengaluru, India, 2023, Pp. 1-7, Doi:10.1109/Easct59475.2023.10392490.

[2] B. Radjaa, L. Nabila And H. B. Salameh, "Federated Deep Learning-Based Intrusion Detection Approach For Enhancing Privacy In Fog-Iot Networks," 2023 10th International Conference On Internet Of Things: Systems, Management And Security (Iotsms), San Antonio, Tx, Usa, 2023, Pp. 156-160, Doi: 10.1109/Iotsms59855.2023.10325826.

[3] E. Bandara, S. Shetty, A. Rahman, R. Mukkamala And X. Liang, "Moose: A Scalable Blockchain Architecture For 5g Enabled Iot With Sharding And Network Slicing," 2022 Ieee Wireless Communications And Networking Conference (Wcnc), Austin, Tx, Usa, 2022, Pp.1194-1199, Doi: 10.1109/Wcnc51071.2022.9771885.

[4] G. Amel And Z. Soraya, "Enhancing Security And Privacy Measures In Internet Of Things (Iot) Implementations," 2024 8th International Conference On Image And Signal Processing And Their Applications (Ispa), Biskra, Algeria, 2024, Pp. 1-6, Doi: 10.1109/Ispa59904.2024.10536814.

[5] M. Chemmakha, O. Habibi And M. Lazaar, "A Novel Hybrid Architecture Of Conditional Tabular Generative Adversarial Network And 1d Convolution Neural Network For Enhanced Attack Detection In Iot Systems," 2023 Sixth International Conference On Vocational Education And Electrical Engineering (Icvee), Surabaya, Indonesia, 2023, Pp. 156-161, Doi: 10.1109/Icvee59738.2023.10348290.

[6] P.Baniya,A.Agrawal,K.Abid,J.Nath,B.K.Ch Audhary And B.Kunwar, "The Internet Of Things: Security Challenges And Opportunities," 2024 3rd International Conference On Power Electronics And Iot Applications In Renewable Energy And Its Control (Parc), Mathura, India, 2024, Pp. 153-158, Doi: 10.1109/Parc59193.2024.10486356.

[7] P. Bhale, D. Ray, S. Biswas And S. Nandi, "Womn: Wormhole Attack Detection And Mitigation Using Lightweight Distributed Ids In Iot Network," 2023 Ieee Guwahati Subsection Conference (Gcon), Guwahati, India,2023, Pp. 01-06, Doi: 10.1109/Gcon58516.2023.10183505

[8] Jablaouiandn.Liouane,"An Effective Deep C Nn- Lstm Based Intrusion Detection System For Network Security," 2024 International Conference On Control, Automation (Iccad), Paris, France, 2024, Pp. 1-6, Doi: 10.1109/Iccad60883.2024.10553826 .

[9] Gupta And G. Singh, "An Empirical Study Of Iot Technology To Enhance Data Breaches And Critical Protective Methods Via Various Correlation," 2022 11th International Conference On System Modeling & Advancement In Research Trends (Smart), Moradabad, India, 2022, Pp. 334-338, Doi: 10.1109/Smart55829.2022.10047668.

[10] Racherla, P. Sripathi, N. Faruqui, M. Alamgir Kabir, M. Whaiduzzaman And S. Aziz Shah, "Deep-Ids: A Real- Time Intrusion Detector For Iot Nodes Using Deep Learning," In I. Eee Access, Vol. 12, Pp. 63584-63597, 2024, Doi: 10.1109/Access.2024.339646.