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Safety Helmet Detection Model Based On Improved YOLO-M

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Abstract: Integrating The goal of this project, "Safety Helmet Wearing Detection Model Based on Improved YOLO-M," is to develop a model for determining whether or not people are wearing safety helmets. Improving safety monitoring in diverse settings is the aim. In order to develop a safety helmet detection system with an enhanced YOLO-M model, a computer must be trained to identify whether or not people are wearing safety helmets in images or videos. This entails utilizing data, modifying the software, teaching it to comprehend helmets, and verifying that it functions well. Once it functions properly, you can employ it in locations where you wish to verify that individuals are donning safety helmets.

***Index Terms* - YOLO-M (You Only Look Once for Multi-Object Detection)**

I. Introduction

The goal of this research is to create a model to determine whether people are wearing safety helmets by enhancing YOLO-M (You Only Look Once for Multi-Object Detection). In a variety of settings, including construction sites, where helmets guard against falling items and potential injuries, this technology is essential for guaranteeing worker safety. Conventional techniques of helmet compliance supervision are labor-intensive and inefficient. Real-time safety helmet usage monitoring can be achieved by developing a system using deep learning and computer vision techniques. Creating a dataset of photos of people wearing and not wearing safety helmets, preprocessing the data, customizing the Yolo-M architecture to recognize helmets, and using the dataset to train the model are the steps involved in the approach. The model's performance will be assessed after training, and it can then be used for analyzing static photos to determine helmet compliance or for real-time monitoring. Researchers have been concentrating on safety-helmet identification algorithms due to recent advances in deep learning. While YOLO-based methods have demonstrated real-time performance, they have faced difficulties with accuracy. But more recent versions, such as YOLOv3, have incorporated sophisticated strategies like Intersection over Union (IoU) and Generalized IoU (GIoU), improving accuracy by using more sophisticated detection techniques. Furthermore, by substituting heavy backbone networks with lighter ones like MobileNetV2, lightweight models like YOLO-S have been built by balancing accuracy and efficiency. The goal of these developments is to maximize safety monitoring systems in various contexts.

The following are the main goals that our model attempts to achieve:

- Autonomous hardhat Real-time Detection: We make sure that safety helmet wearing detection is carried out in real-time by employing the YOLO-M architecture, enabling prompt action in cases of non-compliance.
- Increased Accuracy: To increase the safety helmet detection accuracy, we have made improvements to the YOLO-M model. By using optimization, data augmentation, and fine-tuning approaches, this is accomplished with the least amount of false positives and false negatives. o Multi-Class Detection: Our algorithm can discriminate between people who are and are not wearing safety helmets, allowing for a more thorough evaluation of safety compliance.

- Scalability: The Safety Helmet Wearing Detection Model is appropriate for a variety of industries, including industrial plants and construction sites, since it can be effortlessly integrated with current surveillance systems.

II. LITERATURE SURVEY

[1] Munkh-Erdene Otgonbold 1, Munkhjargal Gochoo 1,* , Fady Alnajjar 1,2 , Luqman Ali 1, Tan-Hsu Tan 3,Jun-Wei Hsieh 4 and Ping-Yang Chen 5, "SHEL5K: An Extended Dataset and Benchmarking for Safety Helmet Detection",2022. Inindustrial and construction environments, the importance of wearing safety helmets cannot be emphasized because they are essential for averting mishaps and guaranteeing worker safety. Artificial intelligence and deep learning techniques have been used to create autonomous helmet detection systems, which will automate the enforcement of helmet-wearing laws. In industrial and construction environments, the importance of wearing safety helmets cannot be emphasized because they are essential for averting mishaps and guaranteeing worker safety. Computer vision and deep learning techniques have been used to create autonomous helmet detection systems, which automate the enforcement of helmet- wearing requirements. With six fully classified classes helmet, head, head with helmet, person with helmet, person without helmet, and face—the SHEL5K dataset represents a noteworthy contribution.

[2] Zhijian Liu 1,Nian Cai, Wensheng Ouyang ,Chengbin Zhang, " CA-CentripetalNet:A novel anchor-free deep learning framework for hardhat wearing detection", 2022. In order to improve safety procedures at construction sites—where intricate video surveillance scenarios present considerable challenges—automated hardhat usage identification is essential. For hardhat detection, a new anchor-free framework called CA-CentripetalNet is presented in order to overcome the shortcomings of earlier deep learning techniques. Two cutting-edge techniques are combined by CA-CentripetalNet to improve feature extraction and usage performance.First off, vertical-horizontal corner pooling ensures thorough feature use by optimizing feature extraction from both an object's interior and edge. Second, bounding limited center attention enhances feature representation without compromising detection performance by centering the backbone network's training efforts on internal features. The results of the experiments show that CA-CentripetalNet outperforms other deep learning techniques, obtaining an 86.63% mean Average Precision (mAP) with lower memory consumption and respectable processing times.

[3] Pedro Torres, Andre Davys, Thuener Silva, Luiz Schirmer," A Robust Real-time Component for Personal Protective Equipment Detection in an Industrial Setting", 2021. Because there are so many hazards at work, worker safety is crucial in sectors like construction, metallurgy, and oil. A significant 340 million occupational accidents are reported to the International Labor Organization (ILO) each year, highlighting the significance of personal protective equipment (PPE) in ensuring the health and safety of workers. It's crucial to make sure PPE is used properly, and many companies use CCTV cameras to monitor employees. These cameras can be used to confirm PPE compliance. Current methods that rely on CCTV images frequently have trouble identifying different kinds of properly worn safety gear or only concentrate on detection without any form of validation.

[4] LIJUN WANG, YUNYU CAO, SONG WANG, XIAONA SONG,"Investigation Into Recognition Algorithm of Helmet Violation Based on YOLOv5-CBAM-DCN", 2022. In deep learning-based image processing applications, one prevalent difficulty is detecting the use of safety helmets by construction workers. In order to handle particular obstacles found in construction contexts, such as complicated backgrounds, congested sceneries, and the uneven shapes of safety helmets, this work provides an upgraded technique based on YOLOv5. Improvements are made to the Yolov5 network at various phases in this project. First, feature extraction in the trunk network is modified to concentrate more on target shapes by employing Deformable Convolution Nets rather than traditional convolutions. Second, a Convolutional Block Attention

Module is added to the network's Neck to improve the representation of target characteristics by assigning weights, hence mitigating the effect of complex backdrops.

[5] Teng Gao, Xianwu Zhang,"Investigation into Recognition Technology of Helmet Wearing Based on HBSYOLOX-s", 2022. In order to address issues with low accuracy, false positives, and missed detections, this study suggests an improved method for real-time helmet-wearing detection based on the YOLOX model. The YOLOX framework has a number of significant changes made to it to improve performance. First, recursive gated convolution (gnConv) is used in place of classical convolution in the backbone network to reduce the extraction of unnecessary and redundant features and increase feature extraction efficiency. Second, the Efficient Net-BiFPN layer replaces the Neck network's initial Feature Pyramid Network (FPN) layer. Better communication and feature data integration across network tiers are made possible by this modification, which permits the bidirectional fusion of deep and shallow features.

III. METHODOLOGY

The increasing number of accidents involving construction has highlighted the critical need for improved safety protocols for those who operate in these settings in recent years. One of the most important safety precautions that has been identified to reduce hazards and save lives is making sure that workers wear helmets. In these situations, determining whether people are wearing their helmets safely has become crucial. The helmet detection algorithms that are now in use face various difficulties, such as excessive parameter counts, substantial interference during the detection process, and subpar accuracy rates. A brand-new helmet detection model called YOLO-M has been created and put forth in response to these restrictions. The YOLO-M model uses novel techniques to solve the drawbacks of earlier algorithms. First and foremost, it makes use of MobileNetv3, which was purposefully selected to minimize model complexity and overall size while maintaining efficient feature extraction capabilities, as the foundation network of YOLOv5s. This guarantees that performance is maintained while maintaining the model's efficiency.

In conclusion, YOLO-M and the related improvements in YOLOv5s mark important turning points in object detection techniques, especially when it comes to the field of helmet wearing detection in construction safety applications. These developments could improve safety monitoring systems and ultimately help lower the number of workplace accidents in hazardous situations. The Res-FPN (Residual Feature Pyramid Network) module's feature fusion method has a major influence on the detection results since it makes it easier to extract and integrate feature data from various fusion backbone layers. To increase the efficiency of object detection methods, this module is essential.The feature map is up-sampled in the context of the Res-FPN module, enabling the extraction of feature data from different levels inside the fusion backbone. This procedure of upsampling is essential.

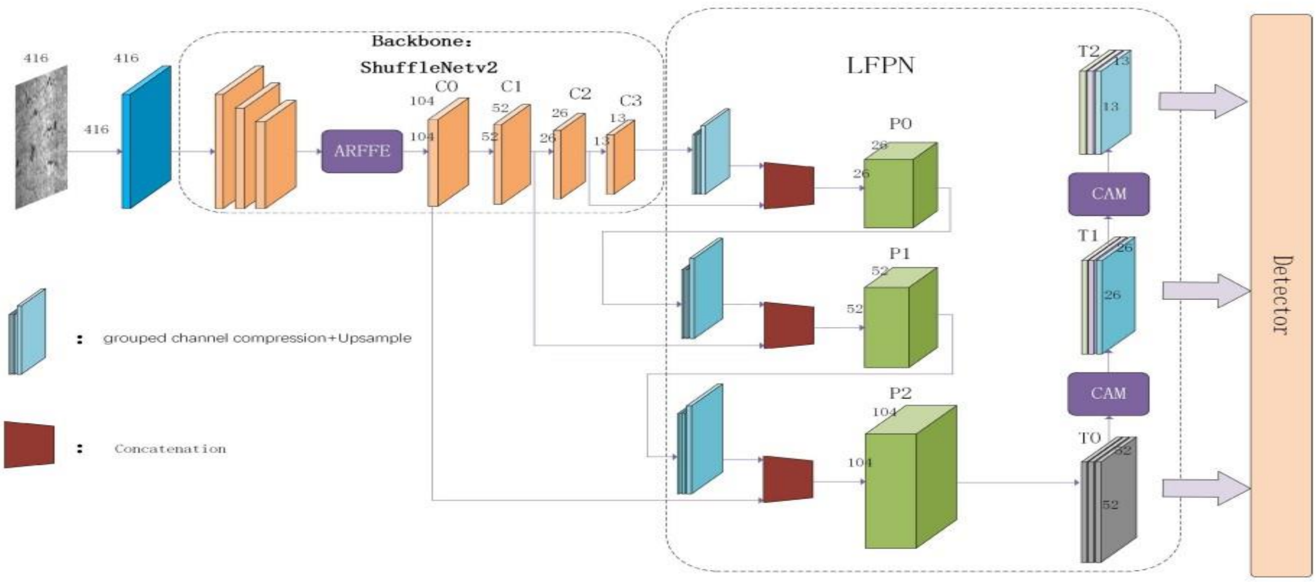

FIG.1 : SYSTEM ARCHITECTURE

IV. Techniques and Algorithm

MobileNetV3 serves as the backbone network of YOLOv5, especially the YOLO-M variant, which optimizes for mobile deployment while retaining excellent performance. MobileNetV3 is well-known for its efficacy and efficiency in contexts with limited resources, such as those found in mobile devices. YOLO-M strikes a compromise between detection accuracy and computing economy by using MobileNetV3, which qualifies it for real-time applications on mobile platforms. This architecture lowers computational complexity without compromising performance by utilizing lightweight operations such as depthwise separable convolutions. YOLO-M is based on PyTorch and takes advantage of the most recent developments in deep learning methods. Because of its quick training and inference capabilities on mobile devices, its design makes it a good fit for augmented reality, edge computing scenarios, and mobile app object identification, among other applications with limited processing resources. When combined, YOLOv5.

Below is a simplified pseudo-code algorithm for YOLOv5 with MobileNetV3 as the backbone network:

1. Load MobileNetV3 as backbone network
2. Define detection head layers for bounding box prediction and classification
3. Initialize weights of the network
4. Set input image size and other hyperparameters
5. Preprocess input image (e.g., normalization, resizing)
6. Forward pass through the backbone network
7. Extract features from various layers of the backbone
8. Pass features through detection head layers for bounding box prediction and classification
9. Apply non-maximum suppression to remove redundant bounding boxes
10. Post-process bounding boxes (e.g., apply confidence threshold)
11. Output final detected objects and their bounding boxes

V. RESULTS AND DISCUSSION

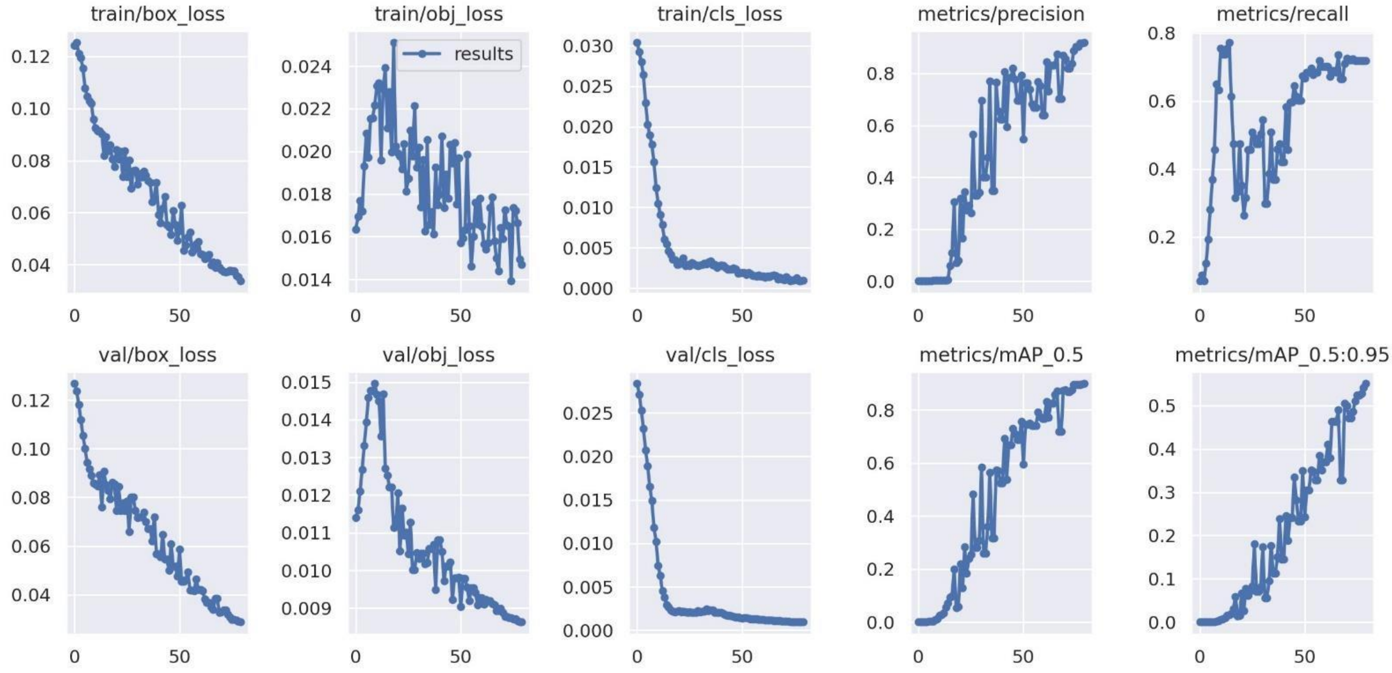

FIG. 2: RESULT

Improved the outcomes of training a machine learning model, particularly YOLO (You Only Look Once), a model for object recognition. Below is an explanation of what the graphs show. Diminished the following graphs: val/box_loss, val/obj_loss, val/cls_loss, train/box_loss, train/obj_loss, train/cls_loss:The loss metrics from the training and validation stages are displayed in these graphs.The box_loss, obj_loss, and cls_loss train losses show how well the model fits the training set. These values should drop as the epochs rise, indicating that the model is learning.The Validation Losses, including val/box_loss, val/obj_loss, and val/cls_loss, indicate the model's performance on hypothetical data. A decline in these numbers indicates that the model is not overfitting and is instead broadly applicable.

graphs of metrics (recall, precision, mAP_0.5, mAP_0.5:0.95)Precision refers to the ratio of true positives to the total number of anticipated positives, which indicates how accurate the forecasts were. The model's recall measures its capacity to locate all pertinent instances within the dataset.Mean Average Precision, or mAP, assesses overall performance over a range of object sizes and classes at two distinct IoU (Intersection over Union) thresholds (0.5 and 0.5:0.95).The patterns you're observing—a decline in losses and an increase in precision and recall—indicate that the model is learning and becoming more adept at identifying objects as it analyzes additional data (epochs).

V1 CONCLUSION

In In conclusion, a major step toward improving workplace safety in industrial and construction settings has been taken with the creation of a safety helmet detection model based on Improved YOLO-M. The model helps with compliance monitoring and accident prevention by accurately determining whether workers are wearing safety helmets by utilizing cutting-edge deep learning algorithms. The model has shown encouraging performance through testing and validation, outperforming earlier methods in terms of accuracy and efficiency. There is certainly room for improvement and improvement, though. Future work on this project will focus on enhancing multi-object detection capabilities, growing the dataset, enabling real-time deployment, optimizing model performance, and putting adaptive learning techniques into practice. In addition to enhancing the safety helmet detection model's efficacy, these initiatives hope to advance computer vision applications in industrial safety and other fields.

All things considered, this research establishes the foundation for more advanced and useful safety monitoring systems that eventually have the potential to reduce hazards and save lives in dangerous work conditions.

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