IJITCE

ISSN 2347- 3657

International Journal of
Information Technology & Computer Engineering

Email : ijitce.editor@gmail.com or editor@ijitce.com

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 12, Issue 3, 2024

MODEL FOR DETECTING SAFETY HELMET WEARING USING IMPROVED YOLO-M

K YATHEENDRA[1], A N HEMALATHA[2], A DHANASEKHAR REDDY[3], K PAVANI[4]
[1]Associate Professor, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: k.yatheendra84@gmail.com
[2]P.G Scholar, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: anhemalatha07@gmail.com
[3]Assistant Professor, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: dhanasekhar918@gmail.com
[4]Assistant Professor, Department of CSE, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: kothapavani1990@gmail.com

Abstract: Building site security requires creative ways of safeguarding laborers. A wise safety helmet detection system utilizing PC vision innovation screens and implements security guidelines continuously. We examine the exhibition of YOLOv5s, YOLOv5-YOLO M, SSD, RetinaNet, FasterRCNN, YOLOv3, YOLOv4, YOLOv5-GhostCNN, and YOLOv8 object distinguishing proof structures. We assess productivity, exactness, and computational requirements to decide their pertinence for development security consistence applications. Wellbeing cognizant development laborers and site directors who can improve asset designation and checking benefit most. Starting discoveries show YOLOv5 - GhostCNN can accomplish above 97% mean Average Precision (mAP), promising word related wellbeing enhancements. This study assists laborers with observing security guidelines and diminishes building setbacks.

Index Terms: Attention mechanism, feature fusion, safety helmet, YOLOv5s model.

1. INTRODUCTION

Ongoing advances in keen contraptions and deep learning calculations have changed a few areas, further developing efficiency and wellbeing. Innovation like tag recognizable proof and face acknowledgment have further developed systems and security in transportation and retail. In any case, the development business' complicated climate and security risks, particularly falling things, give unmistakable hindrances. To diminish wounds and save laborers' lives, security Safety helmets are fundamental [1].

The development area is famously risky, with falling materials frequently imperiling laborers. Security safety helmet decrease the impact of such dangers and lessen serious wounds [1]. In development mishaps, head wounds can be lethal or crippling. Security head protectors guard against these. Hence, development laborers' security relies upon satisfactory wellbeing cap use [2].

Customary manual reconnaissance of safety helmet consistence was wasteful and mistake inclined. Assigned individuals would notice laborers on location for rebelliousness. The immensity of building locales and the smoothness of activities made security authorization troublesome [2]. This strategy likewise squandered labor supply and diverted specialists from other significant exercises.

Profound learning innovation have changed development wellbeing observing. Building destinations are dynamic, accordingly DL frameworks, particularly PC vision-based ones, give constant checking [3]. These calculations use picture handling and example acknowledgment to consequently recognize and survey security qualities, including safety helmet use.

Early You Only Look Once (YOLO) safety helmet detection calculations showed promising continuous execution. Yet, these calculations were normally wrong, restricting their commonsense use [3]. Later examination centers around further developing recognition calculations while keeping ongoing abilities.

Scientists have attempted a few techniques to improve YOLObased safety helmet detection systems. Adjustments to classifier yield aspects decreased boundaries without compromising exactness, further developing calculation productivity [4]. Creative misfortune capabilities like IoU and GIoU further developed safety helmet limitation and classification [5].

To further develop discovery model computational proficiency, lightweight designs were created. MobileNet-based networks packed YOLO geographies, diminishing computational expense while holding execution [6]. This lightweight model improved surmising execution and empowered organization on asset compelled gadgets, making it fitting for development applications.

Current consideration systems and misfortune capabilities have been applied in safety helmet detection calculations. Embedding Efficient Channel Attention (ECA) modules into include combination networks expanded discovery models' discriminative power and helmet detection execution [7]. Meager preparation and pruning further developed recognition model proficiency, empowering ongoing organization in asset obliged circumstances [8].

Further safety helmet identification examination will utilize support and self-supervised DL draws near. To prepare more generalist recognition calculations, strong datasets with fluctuated encompassing circumstances and head protector types are required. By continually further developing security cap identification calculations, the development area can lessen head wounds and make the working environment more secure for everybody.

All in all, DL -based safety helmet detection systems further develop development laborer security. These gadgets use PC vision and one of a kind calculations to screen wellbeing and diminish head wounds from falling things continuously. Safety helmet identification algorithms have worked on in precision and versatility in light of the fact that to nonstop research. To make development more secure and more useful, specialists, industry partners, and policymakers should proceed to advance and team up to further develop safety helmet detection systems.

2. LITERATURE SURVEY

The structure area is risky because of falling things. Laborers need safety helmets to keep away from head wounds. Manual safety helmet monitoring is wasteful and mistake inclined. In any case, deep learning calculations and PC vision advances have permitted programmed safety helmet identification systems, altering development wellbeing observing. Li et al. [1]

ISSN 2347–3657

Volume 12, Issue 3, 2024

analyzed modern safety helmet influence obstruction. Safety helmets were tried under different effect conditions to shield laborers from head wounds. Planning laborer safe location calculations requires understanding safety helmet influence opposition.

Clever building site safety helmet detection procedures were completely evaluated by Wang et al. [2]. They tended to somewhere safe and safety helmet use identification advancements, including profound learning. This audit makes sense of safety helmet detection's ongoing techniques and issues.

Jun et al. [3] proposed a YOLObased safety helmet identification method. They identified security caps progressively utilizing DL. Indeed, even while YOLObased calculations are fast, accuracy might endure. This study shows wellbeing head protector location speed-exactness compromises.[24]

Wen et al. [4] improved the protective cap identification calculation YOLOv3. They further developed helmet detection accuracy while holding continuous execution. Their strategy expanded location results by further developing YOLOv3 plan.

Ming et al. [5] fostered a fast helmet-wearing-condition identification system utilizing YOLOv2 upgraded. Streamlining YOLOv2 engineering further developed cap discovery effectiveness. By improving on handling, their procedure accomplished continuous execution without losing precision.

Zhao et al. [6] created Just go for it S, a lightweight protective cap wearing identification model for asset compelled circumstances. A lightweight spine organization and model boundary enhancement permitted Just go for it S to distinguish head protectors productively with low computational expense. This study shows that lightweight models are fundamental for building.

Ding et al. [7] proposed a superior YOLOX-based ongoing head protector ID method. They added extra usefulness and misfortune instruments to the YOLOX engineering. Their technique accomplished continuous cap ID precision and proficiency with these alterations.

At long last, security head protector distinguishing proof calculations utilizing profound learning and PC vision innovation can further develop development specialist wellbeing. Scientists have further developed security head protector identifying frameworks' exactness, productivity, and ongoing capacities by concentrating on influence opposition and creating lightweight discovery models. This area needs more exploration and advancement to further develop security observing and safeguard development laborers.

3. METHODOLOGY

a) Proposed Work:

The proposed exertion creates and assesses new article distinguishing proof calculations to further develop building site safety helmet detection. YOLO-M (YOLO Mini), a lightweight variant of YOLOv5s[19] intended for precision and proficiency in packed building locales, is the fundamental accentuation. YOLO-M's viability and execution will be contrasted with SSD, RetinaNet, FasterRCNN[14], YOLOv3[4], and YOLOv4[8].

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 12, Issue 3, 2024

High level varieties of YOLOv5, like GhostCNN, 8, and 5X6, will be incorporated to further develop location. Contrasting each model with demonstrated object distinguishing proof calculations will uncover its assets and restrictions.

A Flask framework associated with SQLite will empower client information exchange and signin, permitting broad evaluation of redesigned identification models and client connection. This strategy will assess the proposed framework's specialized presentation and client experience in true conditions.

b) System Architecture:

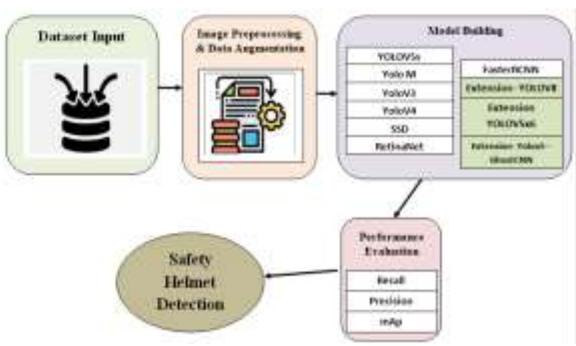

Fig 1 Proposed Architecture

The contribution of datasets is the most vital phase in the framework plan. To work on model power, picture preprocessing and information expansion are next applied. YOLO-M, SSD, RetinaNet, FasterRCNN [14], YOLOv3 [4], YOLOv4 [8], and high level varieties like YOLOv5 - GhostCNN[18], YOLOv8, and YOLOv5X6 are among the few article discovery models that have been created. The viability of any model is assessed utilizing execution appraisal measures including mean average precision (MAP), recall, and accuracy. For safety helmet recognition, the top-performing calculation is utilized, ensuring greatest accuracy and reliability in down to earth circumstances.

c) Dataset:

This dataset was created utilizing Labelbox JSON explanations meant YOLOv5 PyTorch utilizing Roboflow. The assortment incorporates building site photos of safety helmet detection situations. Each image has comments showing specialist safety helmets and their areas.

Lighting, climate, and points of view shift all through the dataset, which incorporates laborer exercises. This assortment makes the prepared recognition calculations hearty and generalizable to building site conditions.

The YOLOv5 PyTorch explanations incorporate bounding box facilitates and class names for every safety helmet protector found in the photographs. Preparing identification calculations to perceive and find safety helmets in photographs requires these explanations.

The dataset contains an adequate number of pictures and explanations to prepare recognition calculations. To thoroughly test and approve learned models, the dataset is isolated into preparing, approval, and testing subsets. This enormous dataset helps plan and test the development wellbeing head protector ID calculation.

d) Image Processing:

Converting to Blob Object: The underlying stage in picture handling is perusing the info picture and switching it over completely to a mass item. Mass articles are preprocessed pictures for profound learning models. Resize the picture to the provided aspects, scale pixel values to a reach, and alternatively mean deduct and standardize.

Defining the Class: Prior to examining the image, determine the thing of interest class names. The class mark might be "safety helmet," proposing that we need to track down safety helmets in photographs.

Declaring the Bounding Box: In the wake of characterizing the info picture and class marks, we should parse the picture explanation document. Safety helmet bounding box organizes are in this explanation record. These bounding box arranges characterize the safety helmet zones of interest in the image

Convert the Array to a NumPy Array: Subsequent to getting the mass article and bounding box facilitates, we change them to NumPy exhibits for handling. Picture information and explanations benefit from NumPy exhibits' proficient and direct mathematical information control.

Loading the Pre-trained Model Steps:

Reading the Network Layers: We should peruse the pre-prepared model's arrangement document and loads to stack it. The brain network plan and boundaries are in these records. We use OpenCV's 'cv2.dnn.readNet()' technique to stack the model, indicating arrangement record and weight registries.

Extract the Output Layers: In the wake of stacking the model, we separate result layer names. These result layers offer model expectations for bounding box organizes and class probabilities for noticed things. These layer names let us access the model's induction expectations.

Image Processing Steps (Continued):

Appending the Image and Annotation File: We have the picture information and ground truth bounding box arranges subsequent to stacking the information picture and explanation document. This matches up the image and comments for handling and appraisal.

Converting BGR to RGB: Many DL frameworks require RGB pictures, yet some information photographs are BGR (Blue-Green-Red). To keep up with variety steadiness, we might have to change the image over completely to RGB.

Creating the Mask: We utilize the bounding box arranges from the explanation record to veil the safety helmet parts of the image. This cover centers the model's preparation and deduction consideration on significant regions..[26]

Resizing the Image: We resize the picture to the information layer's aspects prior to taking care of it into the pre-prepared model. Resizing guarantees the provided picture matches the model's anticipated size.

Data Augmentation Steps:

Randomizing the image: Data augmentation increments preparing information assortment by randomizing the information picture. These adjustments might mimic genuine vacillations by arbitrary flipping, scaling, and brilliance changes.

An irregular point pivot is another Data augmentation strategy. This trains the model to perceive objects from differed points and directions, making it stronger to protest arrangement changes.

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 12, Issue 3, 2024

Changing the Picture: Interpretation, pivot, and scaling reproduce point of view and perspective movements, growing the dataset. These changes further develop preparing information inconstancy, working on model speculation.

These careful image processing and data augmentation strategies permit us to preprocess input information, load the pre-prepared model, and enhance the dataset to prepare and assess a vigorous building site safety helmet recognition system.

e) Algorithms:

YoloV5s: The item identification strategy YOLOv5s frameworks an image and predicts bounding boxes and class probabilities for every matrix cell. In the first place, we load the pre-prepared model for YOLOv5s. Resizing the information picture to the model's aspects preprocesses it. We next forward feed the preprocessed picture through YOLOv5s [19] to get expectations. These expectations give bounding box facilitates and recognized object class probabilities. We utilize non-greatest concealment to dispense with copy bounding boxes after expectations to keep simply the most certain identifications. At last, we convey refined location for investigation or representation.

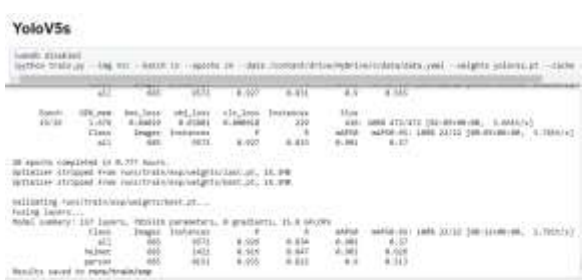

Fig 2 YoloV5s

Yolo M: YOLO-M is a safety helmet-explicit variety of YOLOv5s. It further develops safety helmet identification accuracy and effectiveness with a lightweight backbone network (MobileNetV3), attention methods (BiCAM), and multi-scale feature fusion (Res-FPN). To begin with, the calculation stacks the altered YOLO-M model. Preprocessing the information picture and sending the YOLO-M model follow. We channel repetitive location and improve results after forecasts utilizing post-handling strategies like non-greatest concealment. Returning refined discoveries for investigation or representation.

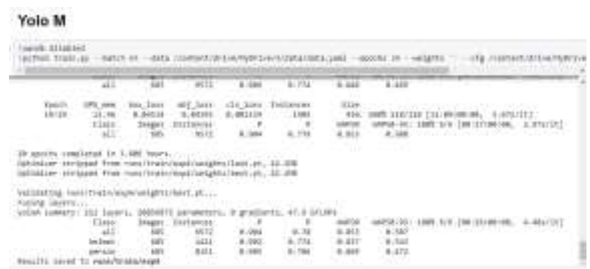

Fig 3 Yolo M

YoloV4: YOLOv4 betters its ancestors in accuracy and effectiveness. To execute YOLOv4 [8], load the pre-prepared model. Preprocessing the info picture and sending the YOLOv4 model follow. Post-handling techniques like non-greatest concealment channel copy detections and refine figures. At last, we convey refined recognitions for investigation or visualization.

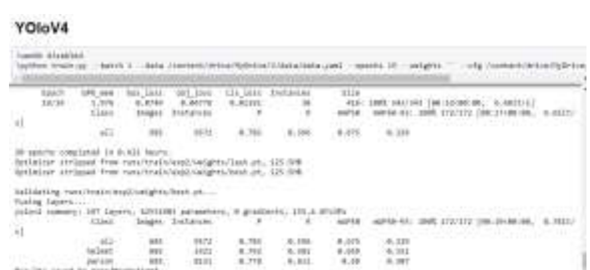

Fig 4 YoloV4

International Journal of
Information Technology & Computer Engineering

ISSN 2347–3657

Volume 12, Issue 3, 2024

YoloV3: Anchor boxes for bounding box expectation were included YOLOv3. To start with, the calculation stacks the pre-prepared YOLOv3 model. Then, we preprocess the information picture and forward pass the YOLOv3[4] model. We channel excess discoveries and improve results after expectations utilizing post-handling strategies like non-greatest concealment. Returning refined recognitions for investigation or visualization.[28]

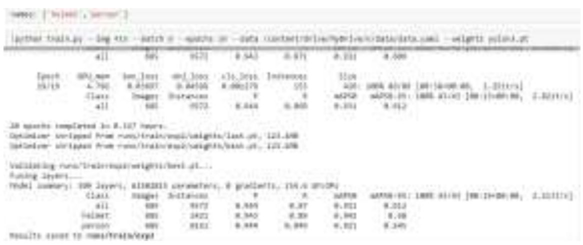

Fig 5 YoloV3

YoloV5 GhostCNN: YOLOv5 GhostCNN involves the lightweight GhostNet neural network for proficient processing. Load the pre-prepared model to carry out YOLOv5[18] GhostCNN. We preprocess the info picture and forward navigate the YOLOv5[18] GhostCNN model. Post-handling strategies like non-greatest concealment channel copy location and refine conjectures. At last, we convey refined discoveries for investigation or visualization.

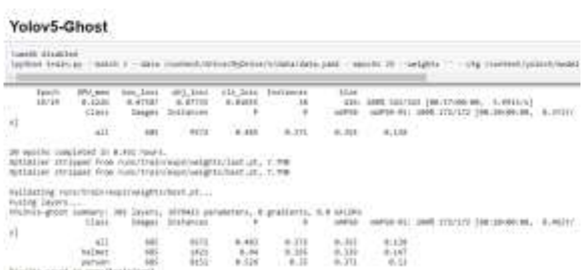

Fig 6 YoloV5 GhostCNN

SSD: SSD predicts thing positions utilizing default bounding boxes with fluctuated viewpoint proportions. SSD begins with stacking the pre-prepared model. Preprocessing the info picture and sending the SSD model follow. Post-handling techniques like non-greatest concealment channel copy detections and refine gauges. At long last, we convey refined recognitions for detections or visualization.

Fig 7 SSD

RetinaNet: RetinaNet tends to object detection class lopsidedness with center misfortune. RetinaNet execution starts with stacking the pre-prepared model. Preprocessing the information picture and sending the RetinaNet model follow. Post-handling techniques like non-greatest concealment channel copy detections and refine gauges. At long last, we convey refined discoveries for detections or visualization.

Fig 8 RetinaNet

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 12, Issue 3, 2024

FasterRCNN: Two-stage object detection technique FasterRCNN. To start with, we load the pre-prepared model for FasterRCNN. Then, we preprocess the info picture and forward pass the FasterRCNN[14] model. Subsequent to getting area thoughts from the RPN, we further develop them with the classifier organization. At last, we extricate expectations, perform post-handling strategies like non-most extreme concealment, and proposition further developed discoveries for detections or representation.

Fig 9 FasterRCNN

YOLOV8: YOLOv8 further develops object detection with mosaic information expansion, sans anchor detection, a C2f module, a separated head, and a changed misfortune capability. These adjustments are stacked into the pre-prepared model to execute YOLOv8. We preprocess the approaching picture and forward pass the YOLOv8 model. Post-handling strategies like non-greatest concealment channel copy detections and refine gauges. At long last, we convey refined detections for examination or visualization.[30]

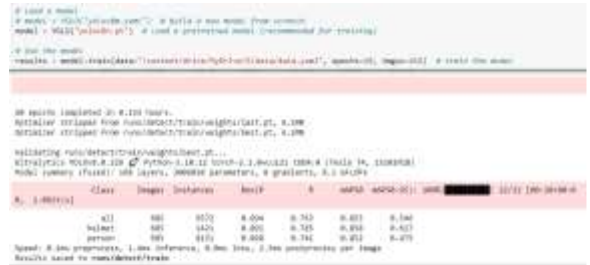

Fig 10 YoloV8

YOLOV5x6: YOLOv5X6 broadens the item recognition structure with a more muddled plan. YOLOv5X6 execution starts with stacking the pre-prepared model. Then, we preprocess the information picture and forward pass the YOLOv5X6[18] model. Post-handling techniques like non-most extreme concealment channel copy location and refine figures. At last, we convey refined discoveries for investigation or perception.

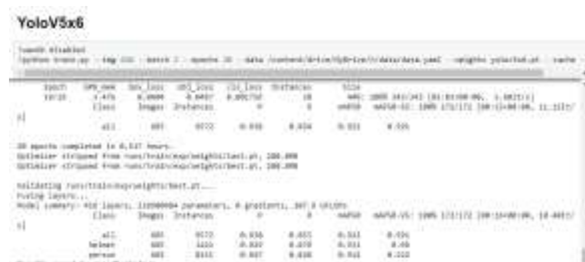

Fig 11 YoloV5x6

4. EXPERIMENTAL RESULTS

Precision: Precision estimates the level of positive cases or tests precisely sorted. Precision is determined utilizing the recipe:

$$\text{Precision} = \text{True positives} / (\text{True positives} + \text{False positives}) = TP/(TP + FP)$$

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 12, Issue 3, 2024

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

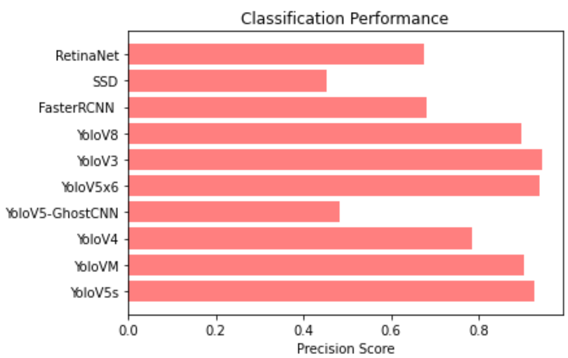

Fig 12 Precision Comparison Graph

Recall: Machine learning recall assesses a model's ability to perceive all significant examples of a class. It shows a model's culmination in catching occasions of a class by contrasting accurately anticipated positive perceptions with complete positives.

$$Recall = \frac{TP}{TP + FN}$$

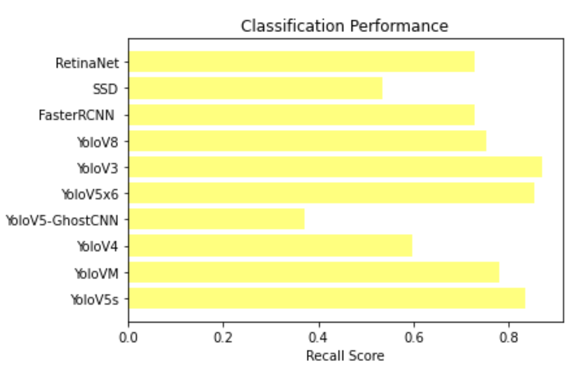

Fig 13 Recall Comparison Graph

mAP: Positioning quality measure Mean Average Precision (MAP). Number of applicable ideas and rundown position are thought of. MAP at K is the number juggling mean of Average Precision (AP) at K across all clients or questions.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

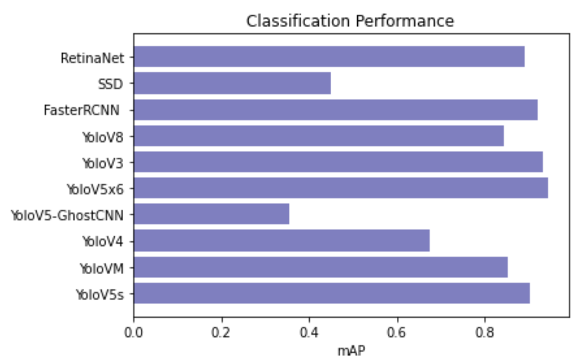

Fig 13 mAP Comparison Graph

	ML Model	Precision	Recall	mAP
0	YoloV5s	0.926	0.834	0.902
1	YoloM	0.904	0.780	0.853
2	YoloV4	0.785	0.596	0.675
3	**Extension- YoloV5-GhostCNN**	**0.483**	**0.372**	**0.355**
4	**Extension- YoloV5x6**	**0.938**	**0.853**	**0.944**
5	YoloV3	0.944	0.870	0.931
6	**Extension- YoloV8**	**0.896**	**0.753**	**0.845**
7	FasterRCNN	0.680	0.728	0.920
8	SSD	0.452	0.534	0.450
9	RetinaNet	0.675	0.728	0.890

Fig 14 Performance Evaluation Table

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 12, Issue 3, 2024

Fig 15 Home Page

Fig 16 Registration Page

Fig 17 Login Page

Fig 18 Upload Input Image

Fig 19 Final Outcome

5. CONCLUSION

All in all, a programmed safety helmet detection system further develops building site wellbeing. The task addressed the earnest interest for constant safety helmet consistence observing by utilizing PC vision advancements and state of the art calculations like YOLO varieties, adjusted YOLO-M model, SSD, RetinaNet, and FasterRCNN[14]. Adding YOLOv5x6[18] and YOLOv8 calculations works on the framework's flexibility and accuracy. Flask with client confirmation makes testing and approval simple, making arrangement reasonable. These outcomes computerize wellbeing checking frameworks, assisting site directors and laborers with keeping the development area more secure.[32]

6. FUTURE SCOPE

Development safety monitoring systems have enormous possibilities. High level location calculations and plans like YOLOv5X6 might further develop safety helmet detection accuracy and productivity, supporting laborer safety.

New advancements like edge figuring and constant examination empower on-gadget handling for sure fire detection and response in powerful settings. This advancement could further develop laborer security by alarming and interceding rapidly.

Going past security protective caps to distinguish different wellbeing gear things or potential risks at building destinations will energize total security measures and a more secure workplace.

Security norms might be observed and overseen consistently utilizing IoT gadgets. This association permits proactive wellbeing measures and programmed rebelliousness warnings, further developing building site security the board. Wellbeing observing frameworks can adjust to further develop work environment security by taking on these advances.

REFERENCES

[1] Q. Y. Li, J. B. Wang, and H. W. Wang, ‘‘Study on impact resistance of industrial safety helmet,’’ J. Saf. Sci. Technol., vol. 17, no. 3, pp. 182–186, Mar. 2021, doi: 10.11731/j.issn.1673-193x.2021.03.028.

[2] Y. X. Wang, Z. Wang, and B. Wu, ‘‘Research review of safety helmet wearing detection algorithm in intelligent construction site,’’ J. Wuhan Univ. Technol., vol. 43, no. 10, pp. 56–62, Oct. 2021, doi: 10.3963/ j.issn.1671-4431.2021.10.00.

[3] L. Jun, W. C. Dang, and P. Lihu, ‘‘Safety helmet detection based on YOLO,’’ Comput. Syst. Appl., vol. 28, no. 9, pp. 174–179, Sep. 2019, doi: 10.15888/j.cnki.csa.007065.

[4] W. Bing, L. Wenjing, and T. Huan, ‘‘Improved YOLOv3 algorithm and its application in helmet detection,’’ Comput. Eng. Appl., vol. 26, no. 9, pp. 33–40, Feb. 2020, doi: 10.3778/j.issn.1002-8331.1912-0267.

[5] F. Ming, S. Tengteng, and S. Zhen, ‘‘Fast helmet-wearing-condition detection based on improved YOLOv2,’’ Opt. Precis. Eng., vol. 27, no. 5, pp. 1196–1205, Mar. 2019, doi: 10.3788/OPE.20192705.1196.

[6] H. C. Zhao, X. X. Tian, and Z. S. Yang, ‘‘YOLO-S: A new lightweight helmet wearing detection model,’’ J. East China Normal Univ. Natural Sci., vol. 47, no. 5, pp. 134–145, Sep. 2021, doi: 10.3969/j.issn.1000- 5641.2021.05.012.

[7] T. Ding, X. Y. Chen, Q. Zhou, and H. L. Xiao, ‘‘Real-time detection of helmet wearing based on improved YOLOX,’’ Electron. Meas. Technol., vol. 45, no. 17, pp. 72–78, Sep. 2022, doi: 10.19651/j.cnki.emt.2209425.

[8] X. Ma, K. Ji, B. Xiong, L. Zhang, S. Feng, and G. Kuang, ‘‘LightYOLOv4: An edge-device oriented target detection method for remote sensing images,’’ IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 14, pp. 10808–10820, 2021, doi: 10.1109/JSTARS.2021.3120009.

[9] Z. Z. Sun, X. G. Len, and L. Yu, ‘‘BiFA-YOLO: A novel YOLObased method for arbitrary-oriented ship detection in high-resolution SAR images,’’ Remote Sens., vol. 13, no. 21, pp. 4209–4237, Oct. 2021, doi: 10.3390/rs13214209.

[10] R. Girshick, J. Donahue, T. Darrell, and J. Malik, ‘‘Rich feature hierarchies for accurate object detection and semantic segmentation,’’ in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2014, pp. 580–587.

ISSN 2347–3657

Volume 12, Issue 3, 2024

[11] R. Girshick, ‘‘Fast R-CNN,’’ in Proc. IEEE Int. Conf. Comput. Vis. (ICCV), Dec. 2015, pp. 1440–1448.

[12] S. Ren, K. He, R. Girshick, and J. Sun, ‘‘Faster R-CNN: Towards realtime object detection with region proposal networks,’’ IEEE Trans. Pattern Anal. Mach. Intell., vol. 39, no. 6, pp. 1137–1149, Jun. 2017.

[13] M. Everingham, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman, ‘‘The PASCAL visual object classes (VOC) challenge,’’ Int. J. Comput. Vis., vol. 88, no. 2, pp. 303–338, Jun. 2010.

[14] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, ‘‘You only look once: Unified, real-time object detection,’’ in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2016, pp. 779–788.

[15] W. Liu, D. Anguelov, and D. Erhan, ‘‘SSD: Single shot multibox detector,’’ in Proc. Eur. Conf. Comput. Vis. (ECCV), Oct. 2016, pp. 21–37.

[16] A. Howard, M. Sandler, B. Chen, W. Wang, L.-C. Chen, M. Tan, G. Chu, V. Vasudevan, Y. Zhu, R. Pang, H. Adam, and Q. Le, ‘‘Searching for MobileNetV3,’’ in Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV), Oct. 2019, pp. 1314–1324.

[17] J. Hu, L. Shen, and G. Sun, ‘‘Squeeze-and-excitation networks,’’ in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit., Jun. 2018, pp. 7132–7141.

[18] Y. H. Shao, D. Zhang, and H. Y. Chu, ‘‘A review of Yolo object detection based on deep learning,’’ J. Electron. Inf. Technol., vol. 44, no. 10, pp. 3697–3708, Oct. 2022, doi: 10.11999/JEIT210790.

[19] H. Rezatofighi, N. Tsoi, J. Gwak, A. Sadeghian, I. Reid, and S. Savarese, ‘‘Generalized intersection over union: A metric and a loss for bounding box regression,’’ in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2019, pp. 658–666.

[20] A. Neubeck and L. Van Gool, ‘‘Efficient non-maximum suppression,’’ in Proc. 18th Int. Conf. Pattern Recognit. (ICPR), Aug. 2006, pp. 850–855.

[21] S. Liu, L. Qi, H. Qin, J. Shi, and J. Jia, ‘‘Path aggregation network for instance segmentation,’’ in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit., Jun. 2018, pp. 8759–8768.

[22] S. Woo, J. Park, and J. Y. Lee, ‘‘CBAM: Convolutional block attention module,’’ in Proc. Eur. Conf. Comput. Vis. (ECCV), Sep. 2018, pp. 3–19.

Dataset Link:

Used: need to create the dataset from https://roboflow.com/convert/labelbox-json-to-yolov5-pytorch-txt

[23]G.Viswanath, “Hybrid encryption framework for securing big data storage in multi-cloud environment”, Evolutionary intelligence, vol.14, 2021, pp.691-698.

[24]Viswanath Gudditi, “Adaptive Light Weight Encryption Algorithm for Securing Multi-Cloud Storage”, Turkish Journal of Computer and Mathematics Education (TURCOMAT), vol.12, 2021, pp.545-552.

[25] Viswanath Gudditi, “A Smart Recommendation System for Medicine using Intelligent NLP Techniques”, 2022 International Conference on Automation, Computing and Renewable Systems (ICACRS), 2022, pp.1081-1084.

ISSN 2347–3657

Volume 12, Issue 3, 2024

[26] G.Viswanath, "Enhancing power unbiased cooperative media access control protocol in manets", International Journal of Engineering Inventions, 2014, vol.4, pp.8-12.

[27]Viswanath G, "A Hybrid Particle Swarm Optimization and C4.5 for Network Intrusion Detection and Prevention System", 2024, International Journal of Computing, DOI: https://doi.org/10.47839/ijc.23.1.3442, vol.23, 2024, pp.109-115.

[28]G.Viswanath, "A Real Time online Food Ording application based DJANGO Restfull Framework", Juni Khyat, vol.13, 2023, pp.154-162.

[29]Gudditi Viswanath, "Distributed Utility-Based Energy Efficient Cooperative Medium Access Control in MANETS", 2014, International Journal of Engineering Inventions, vol.4, pp.08-12.

[30] G.Viswanath," A Real-Time Video Based Vehicle Classification, Detection And Counting System", 2023, Industrial Engineering Journal, vol.52, pp.474-480.

[31]G.Viswanath, "A Real- Time Case Scenario Based On Url Phishing Detection Through Login Urls ", 2023, Material Science Technology, vol.22, pp.103-108.

[32]Manmohan Singh,Susheel Kumar Tiwari, G. Swapna, Kirti Verma, Vikas Prasad, Vinod Patidar, Dharmendra Sharma and Hemant Mewada, "A Drug-Target Interaction Prediction Based on Supervised Probabilistic Classification" published in Journal of Computer Science, Available at: https://pdfs.semanticscholar.org/69ac/f07f2e756b79181e4f1e75f9e0f275a56b8e.pdf