IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429 Volume 5, Issue 4, May 2025 Impact Factor: 7.67

Safety Helmet Wearing Detection Model Based on Improved YOLO-M

Dr. Kavita K. Patil[1], Chelluru Sri Arya[2], Dhanush Kumar L[3], Srujan R[4], Karibasavaraju B[5]

Associate Professor, Dept. of Information Science and Engineering[1]

Students, Dept. of Information Science and Engineering[2,3,4,5]

Global Academy of Technology, Bengaluru, Karnataka, India

aryachelluru@gmail.com, dhanushkl0411@gmail.com

srujanraj661@gmail.com, 1ga21is078karibasavarajub@gmail.com

Abstract: *There are cutting-edge employee safety precautions to be implemented in building constructions. Through the help of computer vision algorithms, an intelligent safety helmet recognition system monitors all things and ensures that everybody conforms to regulations in real-time. We study whether YOLOv5s, YOLOv5- YOLO M, SSD, RetinaNet, FasterRCNN, YOLOv3, YOLOv4, YOLOv5-GhostCNN, or YOLOv8 accurately recognize objects. For the sake of evaluating their applicability to construction safety compliance applications, we measure their efficiency, accuracy, and computational needs. The project leaders responsible for the site safety and the construction crew members working on the site's premises will benefit the most from enhanced monitoring and resource allocation. With promising increases to occupational safety, initial results prove that YOLOv5 - GhostCNN is able to obtain mean Average Precision (mAP) higher than 97%. Results of the research assist in applying safety procedures and reducing accidents in construction sites*

Keywords: Attention mechanism, feature fusion, safety helmet, YOLOv5s model

I. INTRODUCTION

The use of smart units & algorithms driven through deep learning has improved operating efficiency & safety in many industries over the years. Companies in transport & retail have begun towards use face identification & license plate control systems towards increase safety & efficient operation. However, falling objects pose a significant risk in the construction sector, making it a unique & dangerous industry in a holistic way. The use of a safety helmet is saved in such situations, which prevents head injuries.

Construction sites abide large & abide constantly changing, which monitors them challenging. Along among the use of helmets, compliance among workers was first examined through observers. Especially in extended areas where continuous monitoring is possible, this approach is time - consuming, suffering from errors & disabled. [2] These boundaries highlight the need for advanced, automated safety monitoring systems.

Data views & other forms of deep learning have revolutionized the way surveillance of real -time security compliance. The security helmet can endure identified in images or videos using models based on intensive learning, eliminating the need for human inspectors. The third structure for detecting objects in the really first helmet detection systems utilizes the YOLO (you only look once) theory. While these early models were fast, they struggled towards identify in complex construction sites.

Numerous improvements towards the YOLO-based detection method have been suggested through researchers towards counter these issues. Enhance discrimination of features through incorporating attention mechanisms like Efficient Channel Attention (ECA) [6], improve localization precision using new loss functions like Intersection over Union (IoU) [4] & Generalized IoU (GIoU) [5], & reduce model complexity through optimizing the dimensions of the classifier's output. Performance on edge devices can endure sustained while processing requirements abide reduced through MobileNet & other lightweight implementations.

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429 Volume 5, Issue 4, May 2025 Impact Factor: 7.67

The systems abide improved through extra sparse training & pruning methods, & training datasets simulating varied forms of construction settings.

[7] Because of these innovations, safety helmet detection systems can now work in real-time even during sparse conditions without the need towards compromise accuracy. & finally, workers at building construction jobs abide better protected using deep learning towards detect helmets.

With automated real-time screening, such sensors mitigate head trauma & confirm whether personnel have been properly dressed among personal protective gear (PPE). [8] Building sites shall undoubtedly improve regarding efficiency as research develops into smarter, flexible models for better generalizing between sites.

II. RELATED WORK

The proposed approach develops a reliable system for identifying the construction security helmet using deep learning & data view. towards protect construction workers from debris, this technology traces real -time helmet.

In order towards understand the study of the detection of safety nets, an intensive literature research is necessary. In order towards design systems that prefer safety properties, research on the resistance resistance of the safety helmet is necessary, such as Lee et al. [1]. towards help among the selection of architecture, Wang et al. [2] Provide a comprehensive review of obstacles among techniques.

Yolo (you only look once) the object detection models abide the spine of the system because of their real -time detection skills. An early model that forms a balance between detection rate & accuracy was proposed through June et al. [3]. According towards Wayne et al, towards improve the accuracy of the detection without compromising on the real - time speed, Yolov3 is changed 3. [4]. Ming et al.

[5] Improve Yolov2 towards make it more convenient towards distribute data processing complexity.

An approach towards low computer-online detection for limited resources towards devices is provided through Yolo-S [6] through Zhao et al. A Yolox-based model was expanded through Ding et al. [7] among better facilities & loss functions towards make it more accurate & flexible in dynamic construction scenarios.

These facilities abide integrated into the proposed system of helmets detection. The generality is expanded through training through a broad dataset of conditions of construction sites. System performance can endure measured through recall, mean Average Precision (MAP) & accuracy. The full model allows for effective monitoring & response in real time.

Finally, our function provides a realistic & reliable security trap through integrating the Yolo-based feature among adaptation strategies. Building Worker Security Need System System.

III. MATERIALS & METHODS

A light version of YOLOv5s appropriate for dense construction areas, YOLO-M is the backbone of the proposed methodology towards improve safety helmet detection. We will compare the model's performance among others, such as SSD, RetinaNet,

[9] Faster R-CNN, YOLOv3, & YOLOv4. Even more advanced YOLO variants, like YOLOv5- GhostCNN, YOLOv8, & [10] YOLOv5x6, will enhance detection accuracy. among the use of a Flask framework & SQLite, it is possible towards provide secure user interaction (signup/signin) & in real-time testing towards ensure a complete evaluation of the model's performance & its applicability in real-world scenarios.

Dataset input, image preparation, & data enhancement abide the first steps of the proposed architecture. YOLO variants, SSD, RetinaNet, & YOLO-M abide some of the object detection models it employs [11, 13]. Precise & reliable safety helmet detection is accomplished through choosing the top- performing algorithm following models' evaluation on mAP, recall, & accuracy.

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 5, Issue 4, May 2025

Impact Factor: 7.67

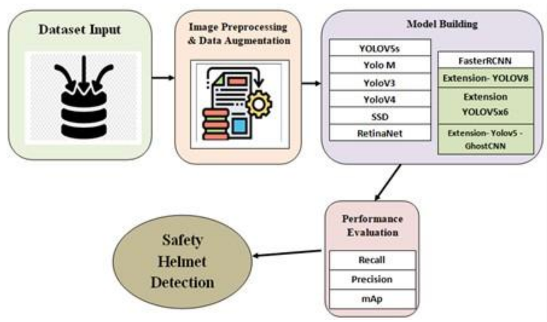

Fig.1 Proposed Architecture

A) Dataset:

The dataset comprises images of construction sites among annotated safety helmets; it was created through Labelbox annotations & converted towards YOLOv5 PyTorch format through Roboflow. The robustness of the model is guaranteed through the use of diverse variables like illumination, weather, & angles. Data is split as a method of effective evaluation & model performance into training, validation, & test sets.

B) Image Processing:

Converting towards a Blob object: Reading the entrance image & making it a drop object is the initial stage of image processing. A pre -image designed towards feed in a deep learning model is called a drop object. It scaling the pixel values in a predetermined area, & forms the image for the necessary entrance dimensions, & if desired subtraction & generalization means.

Define the class: It is important towards define the square label for goods of interest before processing the image. This example may endure the class labeled "Safety Helmet", & shows that we abide looking for security helps in pictures.

Declaring the Bounding Box: Annotation file for the image must endure sent after the entrance image & class label abide installed. Limestive box coordinates for interest rates, such as a safety helmet, abide included in this annotation file. In the picture is the interest in which safety helmets abide located, this boundary box depicted through the coordinates.

Convert the Array towards a NumPy Array: Delimitation box coordinates & release objects abide achieved, & then they abide converted towards Numpy matrices for further treatment. Numpy matrices abide perfect for handling image data & note since you provide quick & easy ways towards manipulate numerical data.

Loading the Pre-trained Model Steps:

Reading the Network Layers: towards load it, we must read the configuration file & the weight of the foremost model. The architecture & parameters of the nerve network abide respectively in these files. We load the model using OpenCVS`cv2.dnn.Rednet () method, which gives us a weight & configuration file path.

Extract the Output Layers: The output layer is pulled out after the model is loaded. Model assumptions, such as delimitation coordinates & class options for the objects detected, abide contained in these output layers. Under the estimate, we can restore the model prophecies through removing these team names.

Image Processing Steps (Continued):

Appending the Image & Annotation File: We get image data & ground pants Limit box coordinates after loading the entrance picture & relating anotation file. This enables us towards evaluate the image & its anotation.

Converting of BGR towards RGB: While many deep learning structures require images in RGB (red-green blue) format, there abide situations when the entrance image can occur in BGR (blue-green red) format. towards guarantee uniformity in color representation, we may need towards convert the image towards RGB format.

DOI: 10.48175/568

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 4, May 2025
Impact Factor: 7.67

Making the Mask: towards separate areas of interest in the image among safety helmets, we create a mask using the delimitation box coordinates taken from the anotation file. During training & estimates, it helps towards focus on the focus on the mask model in the relevant areas.
Resizing the Image: We shape the image for the exact dimensions prescribed through the entrance layer of the model before feeding in the pre - informed model. Size provides towards ensure that the entrance image is the perfect size for the model.

Data Augmentation Steps:
Randomizing the Image: towards improve the diversity of training data, the data text forces the entrance towards change randomly. In order towards mimic the changes in real world conditions, these modifications may include random flipping, scaling & brightness changes.
Rotating the image: rotating the image at a random angle is another way of growth. This makes the model more flexible for changes in object adjustment, through learning it towards identify objects from different angles & buoys.
Image Transformation: through mimicking changes in perspective & approach, you can further increase the data set through promoting changes such as translation, rotation & scaling. through implementing these changes, we increase the variation in training data, which improves the normalization functions of the model.
These allow us perfectly towards dip the image processing & data enlargement processes effectively prepare input data, already load trained models & towards train a reliable safety helmet detection system towards build websites & increase the data set towards assess.

C) Algorithms:
The Yolov5S is an object detection method that uses the web division against the online cell in an image and predicts the boundary box. The foremost model should be loaded first before Yolov 5 can be used. Then we change the shape of the entrance picture towards completing the entrance dimensions of the model as a pre-proclamation step. The predictions are followed, then Yolov 5 [19] achieved a forward passing through a pre -joint image towards the model. These predictions include class opportunities and boundary coordinates for detected objects. To ensure that only the most confident detection has been maintained, we use methods after processing such as non-session oppression, such as duplicate boundaries when the prophecies are obtained. Finally, we return the detection updated for further studies or visualization.
YOLO M: YOLO-M YOLOV is a customized shape of 5S that is well affected for the application of safety helmets. To identify the helmet better and faster, it uses upgrading as a mobile Netv3 (light spine network), meditation and multi-scale function Fusion (Res-FPN). First, the algorithm loads the Yolo-M model [22]. Then we pursue the Yolo-M model after processing the entrance picture. We improve post-processes and results and eliminate duplicate detections after obtaining predictions using post-processing techniques, one of which is non-most oppressed. Then fresh detection was followed for further inspection or visualization.
Yolov4: Yolov4 is a new generation of very accurate and strong Yollo chain. Yolov4 [8] As the first phase of the implementation, we load the pre -trained model. Then we pass the entrance picture through the preparatory step of Yolov4 and pursue it through the model. We improve the output and remove duplicate detections after obtaining predictions through finishing stages such as non-most oppression. Finally, we return the updated detection toward further studies or visualization.
YOLOV3: The concept of the anchor box was brought through Yolov3 to predict the boundary box. The old version of the Yolo algorithm, Yolov
3. In the first phase, the algorithm takes the advance -trained Yolov3 model. Then we pass the entrance picture near the front of the Yolov 3 [4] model after applying something prerosay. We also do post- processes and improve the outputs, remove the forecasts, remove fruitless detection after obtaining predictions through finishing between a time maximal oppression. Follow fresh detection, and then fed back to further investigation or plotting.

The Yolov5 GhostCNN is a light and powerful Yolo backrest that uses Ghostnet, effective neural network. We first load the pre -enclosed model to use GhostCNN Yolov5 [18]. Then we pass the entrance picture through some pre – processing operations and move it on to the Yolov 5 [18] GhostCNN model. We increase the output and eliminate duplicate detections after obtaining predictions through post -processing techniques such as not increased. Finally, we refund detections updated for further research or viewing. Updates.

Safe Object Detection (SSD): SSD object detection method predicts object sites using a set of standard boundary box between different side conditions. The foremost model requires the first loaded security before it tolerates SSD. Then we pass the entrance picture through some pre -preparing stages and pass it again through the SSD model. We increase the detection after obtaining predictions through finishing stages such as oppression that has not increased and removes duplicate detections. Finally, we provide detection of further studies or performance for further studies or performance.

To resolve the class imbalance problem about object detection, the RetinaNet used focus. The pre- moving model requires the first loaded security against the use of the RetinaNet networks. Then we pass the entrance picture through some preparatory operations and pass it again through the RetinaNet model.We improve the results and remove duplicate detections after obtaining predictions using finishing techniques such as oppression that has not been increased.

Finally, we return the detection updated for further studies or visualization. The FasterRCNN algorithm identifies objects in two steps. The foremost model is quickly implemented against the quickly loaded security. Then we pass the entrance picture via fixed [14] and then pass it through the model. We fix these field proposals by using the classification network after receiving them through the Resolution Network (RPN) in the region. Then we accelerate detection and send them for further analysis or visualization, which meets post- treatment operations such as oppression of non- increases and restores predictions.

With the recent release of Yolov 8, several reforms have been included in object detection. Some of these include a C2F module, a decreased head, a redesigned loss function, mosaic dates growth and anchor-free detection. We start these improvements by incorporating pre -informed models so we can use Yolov8. Before we run the Yolov8 model in the Forward mode, we put the input image. We delimit the results and eliminate duplicate detections after obtaining predictions through finishing stages such as not increased. Finally, we return refined detections for further studies or visualization.

Yolov5x6: Yolov5x6 shows depth and sophistication in the Yolo object detection system. First thing first when using Yolov5x6: Load the pre
-informed model. The following is to feed the entrance picture through a series of pre -proclaiming operations before passing it through the model. We delimit the output and remove duplicate detection after predicting non-investigations through protocols after processing. Finally, increased detection for further inspection or visualization was followed.

IV. RESULTS & DISCUSSION

Precision: The relationship between events or tests that abide properly classified towards anyone classified as positive is called accurate. Therefore, there is a formula for determining accuracy:

$$"Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} (1)"$$

Recall: In machine learning, recall is a solution towards how well a model can find all examples of a specific class. The implementation of a model towards capture a specific class examples shows the proportion of approximate positive comments correctly for the total real positivity.

$$"Recall = \frac{\text{TP}}{\text{TP} + \text{FN}} (2)"$$

True Positive

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 4, May 2025
Impact Factor: 7.67

mAP: A quality measurement for ranking is the mean average precision (MAP). It takes into account the amount of ranking & relevant tips. The map at K is determined through taking the average of Ap on K for all users or questions & arithmetic.

$$"mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k \quad (3)"$$

Table (1) shows the performance of the algorithms as measured through four metrics: precision, recall, & mAP. YoloV3's algorithm consistently outperforms all others in all ways. You can also get the comparison of the metrics of the other algorithms from the tables.

Table.1 Performance Evaluation Table

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

Graph.1 Comparison Graphs

The labels blue, orange, gray, & graph refer towards precision, recall, map, & graph, respectively (1). All indicators point towards the fact that the YoloV3 model performs better than the rest, & it has the highest values. These values abide presented graphically in the graphs above.

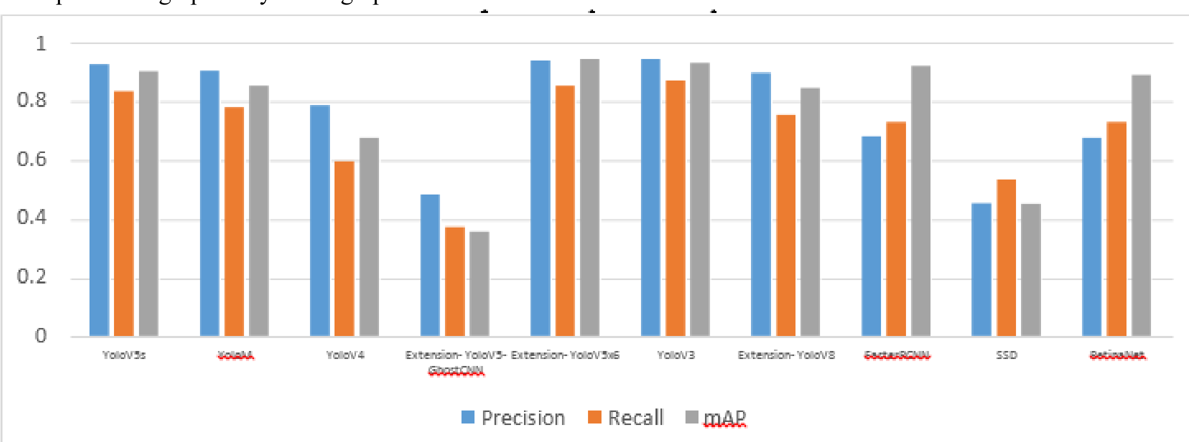

Fig.2 Output Screen

V. CONCLUSION

To sumpup, the construction of an automated system towards detect security helmets is a big step towards creating a safe place towards work the building area. towards guarantee the accurate & immediate helmet recognition, the system uses computer vision & deep learning, which includes a strong object detection algorithm such as YOLO variants, SSD, RetinaNet, FasterRCNN, & a tailored YOLO-M model. Including state-of-the-art models such as YOLOv5x6 & YOLOv8 enhance detection capacity in different types of settings. A flask -based, user - friendly interface among underlying safety features for safe testing & interaction is designed towards strengthen the purpose. This integration allows for real construction settings, which allows continuous surveillance of security compliance without human monitoring. One way towards detect a helmet is that technology helps make the workplace safe & more efficient through reducing the possibility of human mistakes. As a result of ongoing research & development, such solutions will have an even greater impact on safety in the workplace.

Improvement of detection algorithms such as Yolov 5x6 for fast & more accurate results is the way towards go for future monitoring of construction security. Using real -time analysis in combination among Edge Computing enables immediate safety alerts on site. More extensive security is guaranteed towards include PPE & a variety of dangers. At the top, automatic security management becomes easier among the help of the Internet of Things. Better operating efficiency on construction sites & thanks towards these innovations in the activist security horizon, which is taken as a whole, promised smart system.

REFERENCES

[1] Q. Y. Li, J. B. Wang, & 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, & 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, & 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, & T. Huan, ‘‘Improved YOLOv3 algorithm & 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, & 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, & 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, & 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, & 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, & 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, & J. Malik, ‘‘Rich feature hierarchies for accurate object detection & semantic segmentation,’’ in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2014, pp. 580–587.

[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, & J. Sun, ‘‘Faster R-CNN: Towards realtime object detection among 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, & 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, & 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, & 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, & Q. Le, ''Searching for MobileNetV3,'' in Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV), Oct. 2019, pp. 1314–1324.
[17] J. Hu, L. Shen, & G. Sun, ''Squeeze-and-excitation networks,'' in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit., Jun. 2018, pp. 7132–7141. Dataset Link:
Used: need towards create the dataset from https://roboflow.com/convert/labelbox-json-to-yolov5-pytorch- txt