



# IJEAST

INTERNATIONAL JOURNAL  
OF ENGINEERING APPLIED SCIENCE  
AND TECHNOLOGY



**VOLUME : 5    ISSUE : 10    Print / Issue Publication Date: 25-Apr-2021**



**ISSN : 2455-2143**



**DOI : 10.33564/IJEAST.2021.v05i10.036**

Indexed In



[WWW.IJEAST.COM](http://WWW.IJEAST.COM)

[editor@ijeast.com](mailto:editor@ijeast.com)





use the drawings available in this program and improve our documentation to start preparing and maintaining the Keras YOLOv3 model and base download the model to make a new image prediction.

Technical Performance:

Program will use Python and OpenCv to train and reconfigured using YOLO Dataset which freely defined online. Program does require Computer System and GPU to train and perform Object Detection. Program also requires Webcam to re-evaluate objects during re-use of webcam.

● **Economic Access**

Proposed Program requires development tools and software such as PyCharm and KOLO data sets which free of charge online.

For developing the proposed program, we need a various resources such as computer systems, internet connection for help, recommended disk space, and memory speed as mention to the needs of technical. By acquiring all of these features and releasing the proposed app, we have a huge advantage.

III. PROPOSED PROGRAM SUCH ARE

● The existing app does not use the new YOLO Object Versions and algorithms, wheretechnology may not be accurate, up to date, and most of the time. However, the proposed system will be deleted, so we can only recover from the existing system.

● Also with this program new insertion, Therefore, and modification of various data will be very difficult. This program will shock you paperwork. Quality of the dataset will be written So keeping all the above-mentioned benefits and comparing with various expenditures of resources, we conclude that the proposed is economically feasible.

II. MODULES

● **Training Dataset**

One of the most important parts of a machine learning program is to collect high- quality data. You can expect to spend more time on data. Important because our model is the data you only learn from data you only learn from. So how do we teach a machine to get hats? As you can probably guess, by showing many examples.

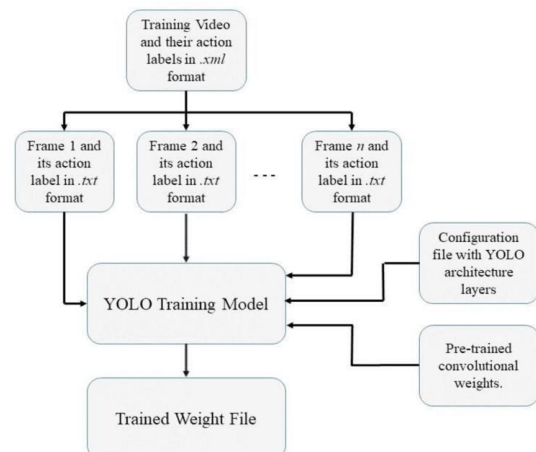
There is a various ways to collect data. When it comes to minges, any of the most popular items use Google Image Search.

● **Label data**

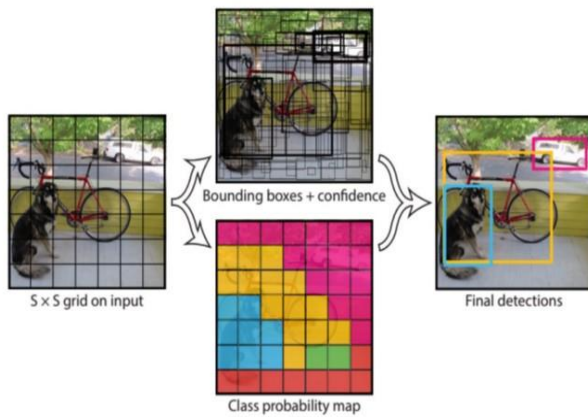
Once the time is up, the next step is to explain/explain it. In the future of discovery, labeling means drawing boxes and objects we wish to find them in pictures and give them a chance to find the corresponding categories / categories of objects so that we need to enjoy the pictures one by looking at high-quality things in hand.

● **Object Discovery**

Camera-yolo3 project provides a wide range of capabilities to use YOLOv3 modes, including object acquisition, transfer learning, and training of new models from cs sc. In this set, we will use model to perform object detection in an invisible view. This functionality is found in a single Python file in a repository named "yolo3\_one\_file\_to\_detect\_them\_all.py" with 435 approximately cables. This text, in effect, will use pre-trained tools to prepare a model and then use model to perform object detection and output modeling. Released on OpenCv. To apply using this program aggressively, we will







- Each grid cell predicts bounding boxes and confidence scores for those boxes. These confidence scores reflect how confident the model is that the box contains an object and also how accurate it thinks the box is that it predicts.
- If no object exists in a cell, its confidence score should be zero.

## VI. EXCEPTIONS

- Yolo can also handle image exceptions and mark them as flags or exceptions.

```

100 # Do inference with given image
101 if FLAGS.image_path:
102     # Read the image
103     try:
104         img = cv.imread(FLAGS.image_path)
105         height, width = img.shape[:2]
106     except:
107         raise Exception("Image cannot be loaded!\n\
108             Please check the path provided!")
109     finally:
110         img, _, _, _ = infer_image(net, layer_names, height, width, img, colors, labels, FLAGS)
111         show_image(img)
112
113 elif FLAGS.video_path:
114     # Read the video
115     try:
116         vid = cv.VideoCapture(FLAGS.video_path)
117         height, width = None, None
118         writer = None
119     except:
120         raise Exception("Video cannot be loaded!\n\
121             Please check the path provided!")
122     finally:
123         while True:
124             grabbed, frame = vid.read()
125
    
```

## VII. LIMITATIONS OF YOLO

- YOLO imposes strong spatial constraints on bounding box predictions since each matrix cell only predicts two boxes and can only have one class.
- This spatial constraint limits the number of nearby objects that our model can predict. Our model battles with

small objects that appear in groups, such as flocks of winged animals.

- Since our model learns to predict bounding boxes from data, it battles to generalize to objects in new or unusual aspect ratios or configurations.
- our model also utilizes relatively coarse features for predicting bounding boxes since our architecture has multiple downsampling layers from the input image.
- Finally, while we train on a loss function that approximates detection performance, our loss function treats errors the same in small bounding boxes versus large bounding boxes. A small error in a large box is generally generous yet a small error in a small box has a much greater effect on IOU.
- The main source of error is incorrect localizations.

## VIII. CONCLUSION

The accuracy of the Object detection in the real world is great and very powerful for many computers and Artificial vision systems. Great progress has been around for the past few years, and the current methods of used equipment have been linked to illegal driving, we are still not happy with the high performance, new driving methods. It should be used instead of being used where it can provide many benefits to the general public.

Robotics, and operating in artificial intelligence technology, the discovery that they can be widely used as drones and other UAVs where detection technology is becoming increasingly common.

## IX. REFERENCES

1. Alvarez-Jimenez, Charkes Daikin. (2013). Why does human vision be superior to any other mammal, 143(1), 143– 149.
2. Anwas Jiwabi., Stip, E., & Kara, N. (2017). Learning Computer Vision through Magic and Python., 12(1), 70– 76.
3. Georgia Razdana, Mukhtar Abbas, Amit Sharma (2018), Classifying everyday objects through computer vision, (13)(1)
4. Ashley Main, Tom Scott, YOLO major advantages of a real computer vision system that generates reliable output.



5. Gaurav Dadhich, Shruti Sambit, Classifying objects based on their outline and greyscale image (2018) (7).
6. D. Erhan, C. Szegedy, A. Toshev, and D. Anguelov. Scalable object detection using deep neural networks. In *Computer Vision and Pattern Recognition (CVPR), 2014 IEEE Conference on*, pages 2155–2162. IEEE, 2014. 5, 6
7. M. Everingham, S. M. A. Eslami, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman. The pascal visual object classes challenge: A retrospective. *International Journal of Computer Vision*, 111(1):98–136, Jan. 2015. 2
8. P. F. Felzenszwalb, R. B. Girshick, D. McAllester, and D. Ramanan. Object detection with discriminatively trained part based models. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 32(9):1627–1645, 2010. 1, 4
9. S. Gidaris and N. Komodakis. Object detection via a multiregion & semantic segmentation-aware CNN model. *CoRR*, abs/1505.01749, 2015. 7
10. S. Ginosar, D. Haas, T. Brown, and J. Malik. Detecting people in cubist art. In *Computer Vision-ECCV 2014 Workshops*, pages 101–116. Springer, 2014.
11. R. Girshick, J. Donahue, T. Darrell, and J. Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. In *Computer Vision and Pattern Recognition (CVPR), 2014 IEEE Conference on*, pages 580–587. IEEE, 2014. 1, 4, 7.
12. R. B. Girshick. Fast R-CNN. *CoRR*, abs/1504.08083, 2015. 2, 5, 6, 7.
13. Prof. Jaima Nelson, Kapur Naman (2017). Object Detection using CNN and Deep CNN., 11(1), 72–76.
14. Anderson Meo, Mustafa Ahmed(2019). Differentiating Ordinary Objects through Computer V, 37, 72–112.

# IJEAST

INTERNATIONAL JOURNAL  
OF ENGINEERING APPLIED SCIENCE  
AND TECHNOLOGY

## ABOUT IJEAST

International Journal of Engineering Applied Science and Technology (IJEAST) is a peer-reviewed, open access journal that publishes high-quality research papers in the field of Engineering, Applied Science and Technology.

IJEAST aims to provide a platform for researchers, academicians, and professionals to share their innovative ideas, research findings, and practical experiences with the global scientific community.

## FOCUS AREAS

- Engineering
- Applied Science
- Technology
- Innovation & Development
- Interdisciplinary Studies



### PEER REVIEWED

All submissions are rigorously peer reviewed to ensure quality.



### OPEN ACCESS

Free and unrestricted access to research for all.



### GLOBAL REACH

Connecting researchers and professionals worldwide.



### TIMELY PUBLICATION

We ensure a swift and efficient publication process.



For more information, visit our website

[www.ijeast.com](http://www.ijeast.com)



INTERNATIONAL JOURNAL  
OF ENGINEERING APPLIED SCIENCE  
AND TECHNOLOGY

✉ [editor@ijeast.com](mailto:editor@ijeast.com)

🌐 [www.ijeast.com](http://www.ijeast.com)

📍 India



2455-2143