International Journal of Future Generation Communication and Networking
Vol.14, No. 1, (2021), pp. 4576- 4581

Helmet Identification of Motorcycle Driver Using CNN

Kunal Raval[1], Namrata Nikam[2], Kunal Khare[3], Kartik Chaudhary[4]

Department of E&TC Engineering, SKNCOE, SPPU, Pune, India

[1]kunalraval79@gmail.com

[2]namrata.nikam_skncoe@sinhgad.edu

[3]kunalkhare09@gmail.com

[4]chaudhari.kartik133@gmail.com

Abstract

To ensure the safety measures, the detection of traffic rule violators is a highly desirable but challenging task due to various difficulties such as occlusion, illumination, poor quality of surveillance video, varying weather conditions, etc. In this paper, we present a framework for the automatic detection of motorcyclists driving without helmets. In the proposed system, we have to detect Motorcyclists wearing a helmet or not, for detecting helmets we used a Tensorflow object detection hence we systematically studied the EfficientDet model which consistently achieves much better efficiency than prior art across a wide spectrum of resource constraints and fined tunned it to detect Helmets.

Keywords—*Helmet Detection, Traffic Surveillance, Tensorflow, Efficientdet*

I. Introduction

Since motorcycles are affordable and a daily mode of transport, there has been a rapid increase in motorcycle accidents since most of the motorcyclists do not wear a helmet which makes it an ever-present danger every day to travel by motorcycle. In the last couple of years alone most of the deaths in accidents are due to damage to the head. Because of this wearing

The helmet is mandatory as per traffic rules, violation of which attract hefty fines. Inspite, a large number of motorcyclists do not obey the rule. Presently, all major cities already deployed large video surveillance networks to keep a vigil on a wide variety of threats. Thus using such an already existing system will be a cost-efficient solution; however, these systems involve a large number of humans whose performance is not sustainable for long periods. Recent studies have shown that human surveillance proves ineffective, as the duration of monitoring of videos increases, the errors made by humans also increase.

Deep networks have gained much attention with state-of-the-art results in complicated tasks such as object recognition tracking detection and segmentation due to their ability to learn features directly from raw data without resorting to manual tweaking.

Tensorflow is a deep learning framework that powers many of the state-of-the-art (SOTA) models in natural language processing (NLP),speech synthesis, semantic segmentation, and object detection. TF2 OD API is an open-sourced collection of object detection models which is used by both deep learning enthusiasts, and by different experts in the field. For the training of the helmet detector, we'll be fine-tuning a pre-trained object detection model from the TF2 Object Detection Model Zoo**.** Specifically, we'll be using EfficientDet D0 512x512 which offers a good trade-off between speed and accuracy.

II. Literature Survey

EfficientDet: Scalable and Efficient Object Detection, the paper describe that the [1] Detection of Motorcyclists without Helmet in Videos using Convolutional Neural Network. The proposed approach tells that using CNN improves the classification performance for both the classification tasks and thus leads to more reliable detection of violators driving without helmets. This major improvement is achieved for the classification of 'Helmet' Vs 'Non-Helmet'.

ISSN: 2233-7853 IJFGCN

Automatic detection of bike riders without helmet using surveillance videos in real-time, In this paper [2] An Enhanced Approach for Detecting Helmet on Motorcyclists Using Image Processing and Machine Learning Techniques. In this paper, They proposed an approach to automatically identify the bike riders who are not wearing helmets. This approach takes video feed from the surveillance camera deployed at roads and applies a background subtraction technique to identify moving vehicles. From the foreground blobs, different features are extracted to identify motorcycles among the other vehicles. From the motorcycle objects, the head region of the blob is considered to extract helmet-related features. For the performance and accuracy improvement, they apply principal component analysis (PCA) on the derived features. To detect helmet from the motorcycle object, different machine learning techniques on the selected features and perform the feasibility analysis.

Passenger compartment violation detection in hov/hot lanes, the paper describe that [7] Safety helmet wearing detection based on image processing and machine learning. In the proposed approach, they uses three phases to detect safety helmet i.e. background modelling, pedestrian classification and finally safety helmet detection. In background modelling ViBe background modelling algorithm is used to detect motion objects under the fix surveillant, after detecting motion objects they used Histogram of gradient (HOG) which explains the inner human and support vector machine (SVM) is used to classify pedestrians. At last colour feature recognition method is used to detect whether the persons wearing safety helmet or not. They also used few machines learning concepts like squeezing out HOG feature and training support vector machine (SVM). The ongoing work of this system is improving accuracy and performance of the algorithms.

III. DATASET

A Dataset is a collection of data. For the training of the model, we used 700 images of a bike rider with a Helmet and Non-Helmet. We have downloaded these images from a goggle datasets search. For the preparation of the dataset to feed the neural network, we have drawn a bounding box using the Label-Img tool and converted its annotations into Pascal/Voc format.

IV. PROPOSED APPROACH

In a proposed approach we have taken a dataset of motorcyclists with and without a helmet. And drawn bounding boxes on helmets of motorcyclists using labelling tool and converted them into Pascal/Voc format, which is required for training. After the bounding box, we have divided the dataset into Training and Testing data in which 75% of data is used for training and 25% data is used for testing.

For this there are using the EfficientDet object detection technique which is developed by “The Google Brain team” recently. EfficientDet model consistently achieves much better efficiency than prior art across a wide spectrum of resource constraints. It uses the fewest training epochs among object detection models. Making it a highly scalable architecture especially when operating with limited computation.Shown below.

Fig. 1 shown the amount of FLOPs(Billions) used to COCO AP. Hyper parameters required for EfficientDet algorithm is mentioned below:

- Num_classes: 2
- Batch_size: 10
- Learning_rate_base: 8e – 3
- Total_steps: 300000
- Warmup_learning_rate: 0.0001

ISSN: 2233-7853 IJFGCN

After setting hyper parameters we have trained EfficientDet object detection on googlecollab with the required dataset and achieved high accuracy. After training, we downloaded all inference graphs to our local system and used them to test the model.

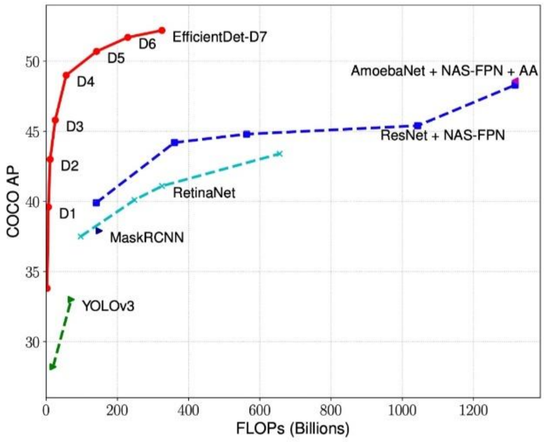

Fig. 1 Amount of FLOPs (Billions) used to COCO AP

V. Proposed METHODOLOGY

Source: The architecture (fig.1) and description of the EfficientDet model is taken from reference [1] which is mentioned in references.

EfficientDet is a single-shot detector fairly similar to the RetinaNet model with several improvements: The efficient net backbone, weighted bi-directional feature pyramid network (BiFPN), and compound scaling method.

The usual approach for improving the accuracy of the object detection models is to either increase the input image size or use a bigger backbone network. Instead of operating on a single dimension or limited scaling dimensions, compound scaling jointly scales up the resolution/depth/width for the backbone, feature network, and box/class prediction network.

EfficientDet models with different scaling factors are included in the TF2 OD API Model Zoo, and the scaling factor is denoted by the *{X}* in the name of the model.

A. *Efficientdet Architecture:*

BiFPN serves as the feature network, which takes level 3-7 features {P3, P4, P5, P6, P7} from the backbone network and repeatedly applies top-down and bottom-up bidirectional feature fusion. These fused features are fed to a class and box network to produce object class and bounding box predictions respectively. Similar to this, the class and box network weights are shared across all levels of the feature.

B. *Compound Scaling:*

a new compound scaling method for object detection, which uses a simple compound coefficient φ to jointly scale up all dimensions of backbone network, BiFPN network, class/box network, and resolution. object detectors have much more scaling dimensions than image classification models, so grid search for all dimensions is prohibitively expensive. Therefore, [1] used a heuristic-based scaling approach, but still, follow the main idea of jointly scaling up all dimensions.

ISSN: 2233-7853 IJFGCN

International Journal of Future Generation Communication and Networking
Vol.14, No. 1, (2021), pp. 4576- 4581

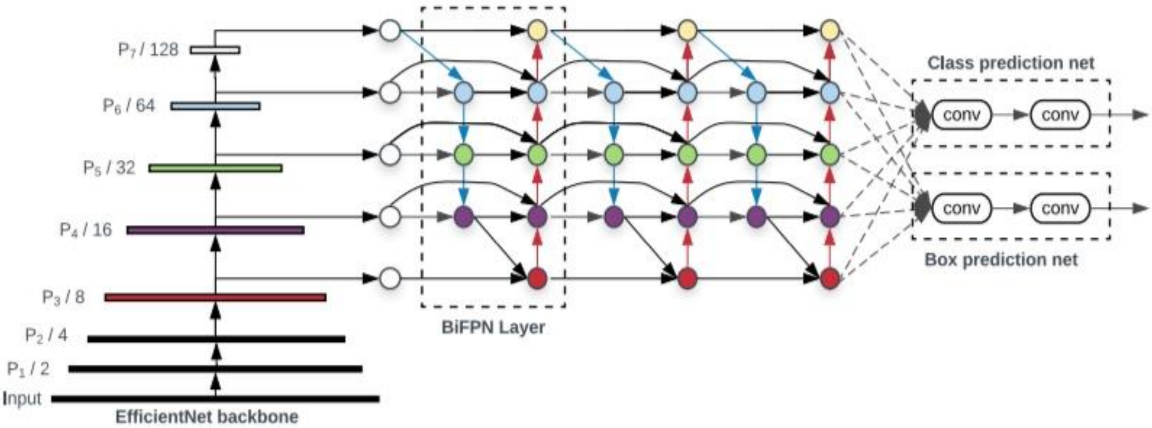

Fig. 2 The architecture of EfficientDet Model

1. Backbone Network: reuse of the same width/depth scaling coefficients of EfficientNet-B0 to B6 such that [1] can easily reuse their ImageNet pre-trained checkpoints.

2. BiFPN: BiFPN is an improved version of the very popular FPN. It learns the weights that represent the importance of different input features, while repeatedly applying top-down and bottom-up multi-scale feature fusion. Formally, BiFPN width and depth are scaled with the following equation:

Wbifpn = 64 ·(1.35), Dbifpn = 3 + φ.…(1)

3. Box/class prediction network: Both BiFPN layers and class/box net layers are repeated multiple times based on different resource constraints

C. EfficientDet architecture

EfficientDet architecture employs EfficientNet as the backbone network, class/box prediction network. Both BiFPN layers and class/box net layers are repeated multiple times based on different resource constraints. Scaling configs for EfficientDet D0-D6 – φ is the compound coefficient that controls all other scaling dimensions; BiFPN, box/class net, and input size are scaled up using equations 1, 2, 3 respectively.

Dbox = Dclass = 3 + [φ/3](2).....(2)

Input image resolution – Since feature level 3-7 are used in BiFPN, the input resolution must be dividable by 2 ^ 7 = 128, so [1] linearly increase resolutions using the equation:

Rinput = 512 + φ · 128(3).....(3)

Following Equations 1,2,3 with different φ EfficientDet-D0 (φ = 0) to D7 (φ = 7) , where D7 is the same as D6 except higher resolution. Notably, scaling is heuristic-based and might not be optimal, but will show that this simple scaling method can significantly improve efficiency than another single-dimension scaling method.

VI. RESULT

For this used TF2 OD API which introduces eager execution that makes debugging of the object models much easier. The new TF2 model Zoo introduces new SOTA models such as EfficientDet. The training has done on googlecolab where google provides free GPU access to users and for storing the dataset we utilized a google drive. In the local system we used Jupyter notebook to test the model using the below libraries:

ISSN: 2233-7853 IJFGCN

Tesorflow: 2.4.1
Python: 3.7.0
Numpy: 1.19.5
Matplotlib: 3.2.2

Fig. 3 Output

VII. CONCLUSION

EfficientDet consistently achieves better accuracy and efficiency than the prior art across a wide spectrum of resource constraints. In particular, scaled EfficientDet achieves state-of-the-art accuracy with much fewer parameters and FLOPs. Hence by using efficientdet we trained helmet, non-helmet data and achieved state-of-the-art accuracy.

REFERENCES

[1] Mingxing Tan Ruoming Pang Quoc V. Le Google Research, Brain Team, “EfficientDet: Scalable and Efficient Object Detection”,CVPR 2020.
[2] K. Dahiya, D. Singh, and C. K. Mohan, “Automatic detection of bike riders without helmet using surveillance videos in real-time,” in Proc. Int. Joint Conf. Neural Networks (IJCNN), Vancouver, Canada, 24–29 July 2016, pp. 3046–3051.
[3] D. Singh, C. Vishnu, and C. K. Mohan, “Visual big data analytics for traffic monitoring in smart city,” in Proc. IEEE Conf. Machine Learning and Application (ICMLA), Anaheim, California, 18–20 December 2016.
[4] MdAmirul Islam, MrigankRochan, Neil DB Bruce, and Yang Wang. Gated feedback refinement network for denseimage labeling.CVPR, pages 3751–3759, 2017.
[5] ZhaoweiCai, Quanfu Fan, Rogerio S Feris, and NunoVasconcelos. A unified multi-scale deep convolutional neuralnetwork for fast object detection. ECCV, pages 354–370, 2016.
[6] GolnazGhiasi, Tsung-Yi Lin, Ruoming Pang, and Quoc V. Le.Nas-fpn: Learning scalable feature pyramid architecturefor object detection. CVPR, 2019.2, 3, 4, 6, 7.

ISSN: 2233-7853 IJFGCN

[7] "Passenger compartment violation detection in hov/hot lanes," IEEE Transactions on Intelligent Transportation Systems, vol. 17, no. 2, pp. 395– 405, 2015.

[8] F. W. Siebert and H. Lin, "Detecting motorcycle helmet use with deep learning," Accident Analysis & Prevention, vol. 134, p. 105319, 2020.

[9] B. Yogameena, K. Menaka, and S. Saravana Perumaal, "Deep learning based helmet wear analysis of a motorcycle rider for intelligent surveillance system," IET Intelligent Transport Systems, vol. 13, no. 7, pp. 1190– 1198, 2019.

[10] F. W. Siebert, D. Albers, U. Aung Naing, P. Perego, and S. Chamaiparn, "Patterns of motorcycle helmet use - A naturalistic observation study in Myanmar," Accident Analysis & Prevention, vol. 124, pp. 146–150, 2019.

[11] R. D. Ledesma, S. S. López, J. Tosi, and F. M. Poó, "Motorcycle helmet use in mar del plata, argentina: prevalence and associated factors," International journal of injury control and safety promotion, vol. 22, no. 2, pp. 172–176, 2015.

[12] D. V. Hung, M. R. Stevenson, and R. Q. Ivers, "Prevalence of helmet use among motorcycle riders in vietnam," Injury prevention, vol. 12, no. 6, pp. 409–413, 2006.

[13] A. M. Bachani, N. T. Tran, S. Sann, M. F. Ballesteros, C. Gnim, A. Ou, P. Sem, X. Nie, and A. A. Hyder, "Helmet use among motorcyclists in cambodia: a survey of use, knowledge, attitudes, and practices," Traffic injury prevention, vol. 13, no. sup1, pp. 31–36, 2012.

[14] H. Lin, "Helmet use detection source code," https://github.com/LinHanhe/ Helmet_use_detection, 2020.

[15] H. Lin and F. W. Siebert, "The HELMET dataset," 2020, https://osf.io/ 4pwj8/.

[16] J. Chiverton, "Helmet presence classification with motorcycle detection and tracking," IET Intelligent Transport Systems, vol. 6, no. 3, pp. 259– 269, 2012.

[17] R. Silva, K. Aires, T. Santos, K. Abdala, R. Veras, and A. Soares, "Automatic detection of motorcyclists without helmet," in 2013 XXXIX Latin American Computing Conference (CLEI). IEEE, 2013, pp. 1–7.

[18] R. Waranusast, N. Bundon, V. Timtong, C. Tangnoi, and P. Pattanathaburt, "Machine vision techniques for motorcycle safety helmet detection," in 2013 28th International Conference on Image and Vision Computing New Zealand (IVCNZ 2013). IEEE, 2013, pp. 35–40.

[19] K. Dahiya, D. Singh, and C. K. Mohan, "Automatic detection of bikeriders without helmet using surveillance videos in real-time," in 2016 International Joint Conference on Neural Networks (IJCNN) IEEE, 2016, pp. 3046–3051.

[20] C. Vishnu, D. Singh, C. K. Mohan, and S. Babu, "Detection of motorcyclists without helmet in videos using convolutional neural network," in 2017 International Joint Conference on Neural Networks (IJCNN). IEEE, 2017, pp. 3036–3041.

ISSN: 2233-7853 IJFGCN