Social Distancing Violation Detection Mechanism Using Opencv

Samarth Sachan, Shreedhar Sharma, Utkarsh Chaudhary and Mukesh Raj

May 12, 2023

SOCIAL DISTANCING VIOLATION DETECTION MECHANISM USING OPENCV: A REVIEW

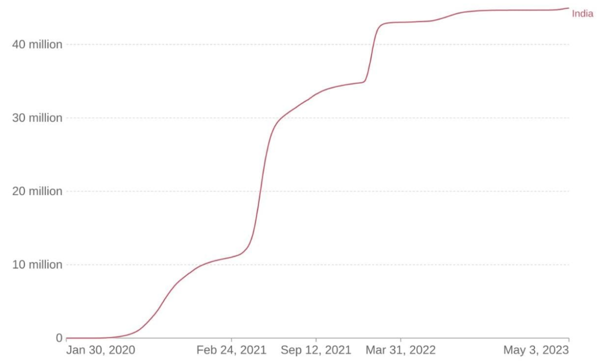
Samarth Sachan[1]	Shreedhar Sharma[2]	Utkarsh Chaudhary[3]	Mr. Mukesh Raj[4]
Department of Computer Science and Engineering	Department of Computer Science and Engineering	Department of Computer Science and Engineering	Department of Computer Science and Engineering
JSS Academy of Technical Education Noida, UP, India	JSS Academy of Technical Education Noida, UP, India	JSS Academy of Technical Education Noida, UP, India	JSS Academy of Technical Education Noida, UP, India
samarthsachan2001@gmail.com	shree.sharma2203@gmail.com	daster735@gmail.com	mukeshraj.2021t@gmail.com

Abstract- To counter the pandemic of Novel CoronaVirus one of the most effective measures was Social Distancing. However, a lack of spatial awareness may unintentionally transgress this new need. In light of this, we suggest a proactive surveillance system to contain the spread of COVID-19. We offer a real-time image-based system that uses deep learning models to identify Social Distancing violations and transmit visual information. The injury probability Social Distancing can therefore approach zero if the pedestrian density stays below a newly defined critical social density threshold, which we then specify. The proposed system is also morally sound. We do not collect information or target specific individuals. There are no administrators working. It can be integrated and used with the cameras installed in the public places to monitor the situation and condition of social distancing.

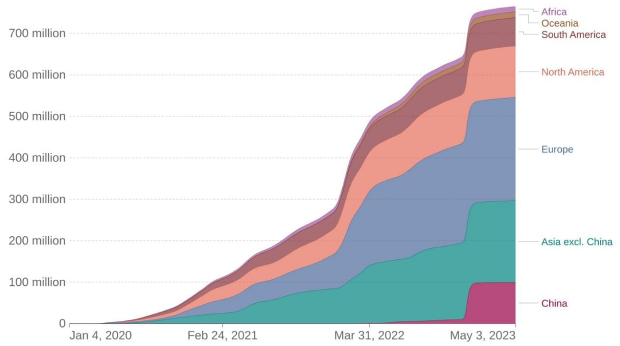
Keywords - Social Distance, Pedestrian Detection, Linear Regression

I. INTRODUCTION

New Coronavirus Disease in 2019 (COVID-19) Pandemic. The people, however, are not accustomed to a fictitious security bubble being created around them. Automated warning systems can aid and raise public awareness [2, 3, 4, and 5]. These active surveillance systems need to be implemented with solid system design and after careful ethical deliberation. Confidentiality is the first problem [6]. An individual's privacy may be violated through the gathering and storage of data purposely or accidentally. As a result, the system is left without the ability to store data and must function in real time. Second, the detector shouldn't make any distinctions. Building an AI-based detection system is the most reliable way to accomplish this. Just keeping humans out of the detection loop is insufficient in some situations. Additionally, the detector must be design-free.
Hand-crafted trait extractors in domain-specific systems can result in dangerous designs. With one exception, connectionist machine learning systems like deep neural networks, which lack a feature-based input field, are far more equitable in this regard. In other words, the training data distribution must be equitable. notifications that are both visual and audible in all directions when social distance violations are found. The suggested approach detects an object by its bounding box within a specified frame of a monocular camera by using a pre-trained model [7,8]. The international community is seeking alternatives to stem the spread of the virus. Those that are in close proximity to one another for an extended period of time (within six feet) are the main carriers of the virus. When a person with the virus sneezes, coughs, or talks, droplets from their mouth or nose travel through the air and infect those nearby. Through the respiratory system, the droplets also enter the lungs, where they begin to destroy lung cells.Recent research demonstrates that those who are infected with the virus but exhibit no symptoms contribute to its transmission as well (W. C. D. C. Dashboard). It is still advisable to keep a minimum of 6 feet between you and other people.In order to prevent the spread of the virus, social distancing involves avoiding large crowds in public areas (such as malls, parks, schools, universities, airports, and workplaces), minimising human physical contact, and maintaining a sufficient distance between individuals.Social isolation is critical, especially for those at higher risk of serious disease from COVID-19. Spread of Covid 19 is as follows[28]:

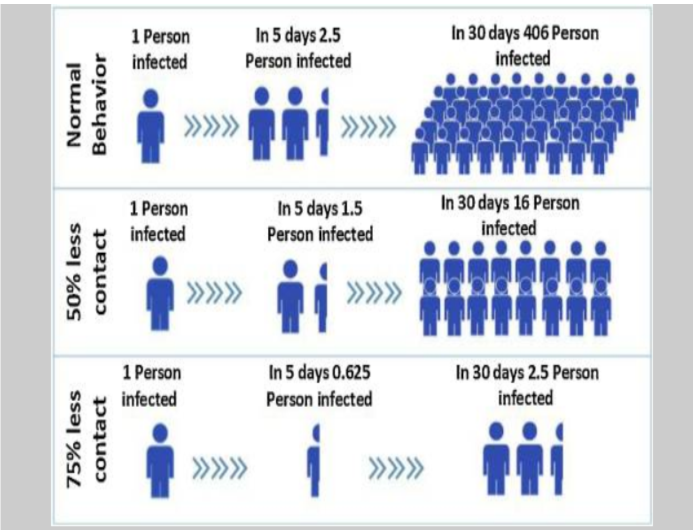


Covid cases in India



Covid cases across Globe

. The spread of the virus and the severity of the sickness can be considerably lowered by lowering the chance of virus transmission from an infected person to a healthy person. It is evident that social isolation can lessen both the cost on healthcare organisations and the number of afflicted people. By ensuring that the number of infected cases (patients) does not exceed the capacity of public healthcare, it also lowers mortality rates.



The technology will provide a visual signal—not an alarm—when a distance below the threshold is detected.

The technology monitors the situation and tells when the social distancing norms are not being followed . Our main contributions are as follows:

- A new real-time vision-based method for detecting social distance and critical social density has been developed.
- Definition and Measurement of Significant Social Density Using Statistical Methods.

In order to monitor social distance and calculate the distance between people, the above perspective improves the field of view and solves the occlusion problem. It could reduce the demand for processing, communication, energy, human resources, and installation expenses.

The purpose of this work is to offer a deep learning-based social distance monitoring framework for the open campus setting. YOLO (You Only Look Once), a deep learning model. The detection model identifies people and provides bounding box data. Following human detection, each identified centroid pair's Euclidean distance is calculated using the discovered bounding box and its centroid information.

II. LITERATURE SURVEY

Since December 2019, significant acute respiratory syndromes have been brought on by social distancing for COVID-19 [9]. Social distance is seen to be the most effective method for preventing the spread of the dangerous virus after the COVID-19 pandemic started in late December 2019 and was adopted as normal practice on January 23, 2020, examining the effects of social distance on the COVID-19 outbreak's spread. According to the studies, social withdrawal should be practised as soon as possible to gradually lessen the peak of a viral attack. As we all know, social estrangement is a painful economic step even if it is essential for flattening the infection curve.

We deduced from the literature that the researcher had put in a lot of effort to track social distance in public settings. However, the frontal or side view camera angle dominates most of the work. The overhead view social distance monitoring framework we presented in this work thus plays a crucial role in social distance monitoring to compute the distance between people by providing a better field of vision and overcoming occlusion concerns.

Recent research indicated that social isolation is a useful tool for controlling the COVID-19 virus's transmission [1]. Maintaining a minimum distance of 2 metres (6 feet) between people in order to prevent potential interaction is known as social distancing. Additional research [10] also reveals that social estrangement provides considerable economic advantages. Although COVID-19 may not be entirely eradicated in the near future, our society would tremendously benefit from an automated system that could monitor and analyse social distancing practices. detection of pedestrians.
Detecting pedestrians can be seen as either a sub-task of general object detection or as a separate task that solely looks for pedestrians. [11] provides a thorough examination of 2D object detectors, as well as the corresponding datasets, metrics, and fundamentals. Another survey [12] focuses on approaches based on deep learning for both generic object detectors and pedestrian detectors. In general, cutting-edge detectors are classified into two types. Two-stage detectors are one type of detector. The majority of them are R-CNN [13], [7], which starts with region proposals and then performs classification and bounding box regression. One-stage detectors are the other type. YOLO [14], [8], SSD [15], and EfficientDet [16] are notable models. The detectors can also be classified as anchor-based [13], [7], [14], [8], [15], or [16] approaches.

The main distinction between them is whether they use a predefined set of bounding boxes as candidate positions for the objects. The datasets of Pascal VOC [19] and MS COCO [20] were typically used to evaluate these approaches. These approaches' accuracy and real-time performance are sufficient for deploying pre-trained models for social distancing detection.

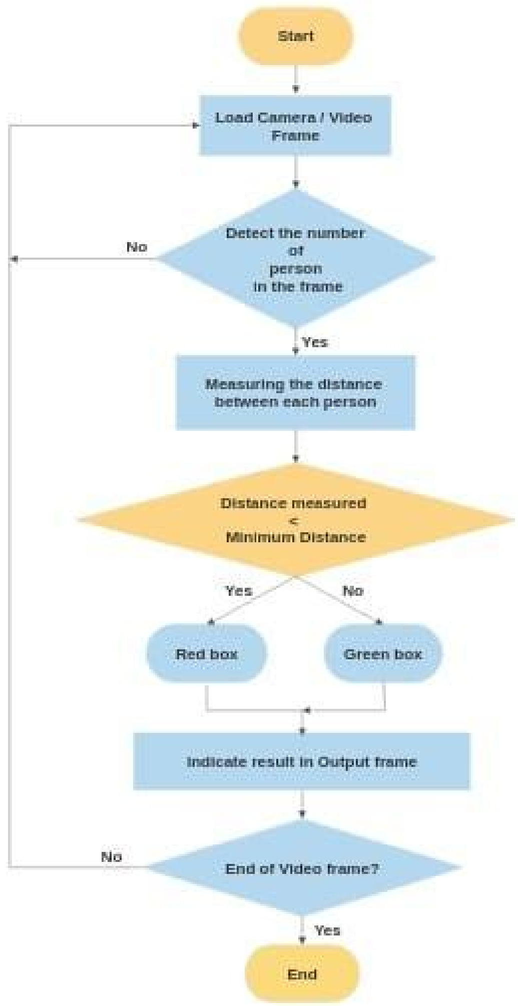
Monitoring of social distance. Emerging technologies have the potential to aid in the practice of social distancing. A recent study [2] found that emerging technologies such as wireless, networking, and artificial intelligence (AI) can enable or even enforce social distancing. The paper discussed potential fundamental concepts, measurements, models, and practical scenarios for social distancing. Another study [3] classified various emerging techniques into human-centric or smart-space categories, along with a SWOT analysis of the techniques discussed. To detect and track pedestrians, a specific social distancing monitoring approach [4] that uses YOLO and Deepsort was proposed, followed by calculating a violation index for nonsocial distancing behaviours. The approach is intriguing, but the results lack statistical analysis. Aside from the violation index, there is no implementation or privacy-related discussion. [5] defines social distancing monitoring as a visual social distancing (VSD) problem. The study presented a skeleton detection-based approach for measuring interpersonal distance. It also addressed the impact of social context on people's social distancing and raised privacy concerns. The talks are motivating, but they once more do not produce conclusive findings for social distance monitoring, leaving the issue open.

Recently, a number of prototypes that make use of sensing and machine learning technologies have been created to aid in social distancing monitoring. A social distance detector developed by Landing AI [21] that uses a security camera to indicate people whose physical proximity falls below the ideal level. In a manufacturing plant, a similar system [22] was installed to track employee behaviour and issue audio alarms in real-time. Other types of sensors than security cameras can also be helpful, as shown by the LiDAR-based and stereo camera-based systems that were also presented.

The aforementioned solutions are intriguing, but some people may object to them since they record data and generate obtrusive alarms. On the contrary, we suggest a visible, non-intrusive warning system with no risk of threat to privacy.

III. WORKFLOW

There are several methods for detecting objects; we use You Only Look Once (YOLO) to detect people and calculate their Euclidean distance.



Flow Chart

Following detection, each bounding box centroid distance is calculated using the bounding box information, namely centroid information. We measured the distance between each identified bounding box of humans using Euclidean distance. Once the centroid distance has been calculated, a predetermined threshold is employed to determine whether or not the distance between any two bounding box centroids is smaller than the specified number of pixels. If two persons are close to one another but their distance value is greater than the required minimum social distance. The model's output shows the overall number of social distance violations as well as any centroids and bounding boxes of people that were found.The newly trained YOLO was also contrasted with other deep learning models. various deep learning models' True detection and False detection rates. As can be observed from the outcomes, transfer learning considerably enhanced the outcomes for the overhead view data set. Different deep learning models have very low false detection rates (approximately 0.7–0.4% without any training), demonstrating their efficacy. On the overhead data set, various pre-trained object detection algorithms are put to the test. Despite being trained on various frontal data sets, the models still perform well, obtaining a 90% accuracy rate. Results of various state-of-the-art detection methods are compared.

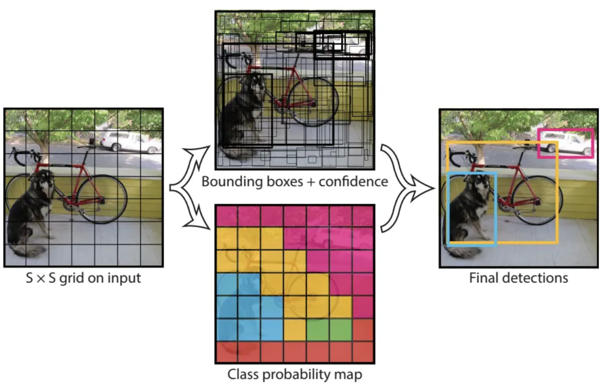
Each centroid's information is kept in the form of a list. A threshold is established based on distance values to determine whether any two individuals are less than N pixels apart. If two persons are too close together or the distance breaches the minimal social distance set, the information is added to the violation set. Initialization sets the bounding box's colour to green. The data is checked against the list of violations; if the current index is present, the red colour is updated. Additionally, the detected people in the video sequence are tracked using the centroid tracking technique. The tracking technology also aids in monitoring those who exceed the social distance limit.

IV. METHODOLOGY

Object Detection

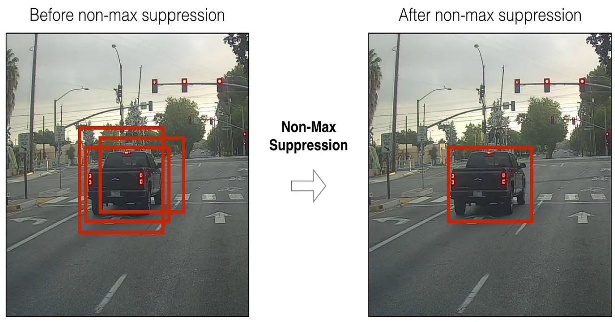
Detecting pedestrians and determining their coordinates is the first and most important task. For object detection we are using the YOLO[26] model. This method can predict the type and location of an object based on a single look at the image. A pre-trained model can only detect objects that resemble humans because it only takes into account the human (person) class. In this network the image is divided into regions and bounding boxes and probabilities for each is forecasted. For each bounding box, the network predicts four coordinates (tx, ty, tw, th). If the cell is offset (cx,cy) from the image's top left corner and the previous bounding box has width and height pw,ph, the prediction is:

$$
\begin{aligned}
b_x &= \sigma(t_x) + c_x \\
b_y &= \sigma(t_y) + c_y \\
b_w &= p_w e^{t_w} \\
b_h &= p_h e^{t_h}
\end{aligned}
$$



Object detection through bounding boxes

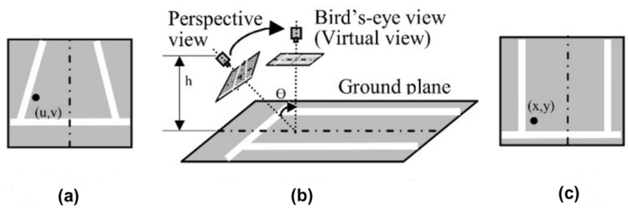
To minimize the issue of various boxes overlapping in the frame during object detection, minimal post-processing is applied like non-max suppression (NMS)[22].



NMS Suppression

Bird eye view

The region of interest (ROI) is then transformed to Bird's eye view to calculate the distance between them. "*getPerspectiveTransform*" is used to convert the perspective into bird eye view and "*warpPerspective*" is used to wrap the transformed view into the original image.



a) perspective view image. b) Perspective transformation. c) Bird's-eye view image

To make the transformation, it is essential to calculate the matrixes, it is known as Inverse Perspective Mapping.This step is necessary because the distance cannot be calculated just by calculating the pixels between the objects. It also gives the flexibility in the positioning of the camera.

Distance between objects

To calculate the distance we use the Euclidean formula using the coordinates of the center of the bounding boxes. Scaling factor is used to compute the real world situation. In this case the distance used is 6 feet (approx. 180 cm). Euclidean formula is as follows:

$$
d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}
$$

If the distance is less than 6 feet than it will alert with the "Red" box, "Yellow" denotes "medium risk", and "Green" denotes "low risk". The colors are used to show the threat level in the video.

Why YOLO

Comparison of YOLOv3 with other models[23][24][29] :

YOLO vs Other algorithms

As for this mechanism, faster detection and better speed is more desirable. YOLO was the right fit for the same.

V. OUTPUT

Objective: To identify the violations of the Social Distancing norms through a video feed in public places and highlighting such violations.

Output image 1

Output image 2

Output image 3

Result: Objective achieved.

a) Violations are detected

b) Count of violations is displayed.

VI. CONCLUSION

We would be able to stave off many different diseases if we could put a lid on the maintenance of social distance. Technology is advancing along with viruses, allowing us to solve a variety of problems. In order to automate monitoring through object recognition and tracking, this research offers a useful computer vision paradigm. Each individual is recognised as an object, and the separation calculated distance between them. This system keeps the situation under control quickly and effectively.

The freedom of movement of people remains unhindered throughout the scene. People in the scene are free to move around, and the camera's position and radial distance have an impact on how they seem visually. From the example frames, it is clear that the visual appearance of humans in the data set varies, as do their heights, positions, and scales. We employed OpenCV for the implementation. The testing results of the pre-trained model are covered in the first subsection, and the results of the detection model after transfer learning and training on the overhead data set are covered in the second subsection. The model is evaluated using the same video clips as a comparison.. The framework effectively recognises individuals who break social distance and are walking too closely, according to experimental data. Additionally, the transfer learning methodology improves the detection model's overall effectiveness and accuracy. Without transfer learning, a pre-trained model obtains detection accuracy of 92%, while with transfer learning, the model achieves detection accuracy of 95%. The model's tracking accuracy is 95%. Future iterations of the work could make it more suitable for various indoor and outdoor settings. Different detection and tracking algorithms may be employed to assist in locating the individual or individuals that violate or cross the social distance threshold.

watched for any warning signs. It might be put to use in congested areas like temples, malls, metro stations, etc.

REFERENCES

[1] https://files.eric.ed.gov/fulltext/ED613955.pdf (2021).

[2] Gardner, M. (2021): HE and research face ‘historic watershed’, says council. https://www.universityworldnews.com/post.php?story=20210204131317236 (Accessed 4 February 2021). .

[3] Adjusting to the New Normal. https://www.purdue.edu/caps/covid19/adjusting-to-new-normal.html (Accessed 22 February 2021).

[4] M. Cristani, A. Del Bue, V. Murino, F. Setti, and A. Vinciarelli, “The visual social distancing problem,” arXiv preprint arXiv:2005.04813,2020.

[5] A. B. Chan, Z.-S. J. Liang, and N. Vasconcelos, “Privacy preserving crowd monitoring: Counting people without people models or tracking,” in 2008 IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2008, pp. 1–7.

[6] S. Ren, K. He, R. Girshick, and J. Sun, “Faster r-cnn: Towards real-time object detection with region proposal networks,” in Advances in neural information processing systems, 2015, pp. 91–99.

[7] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, “Yolov4: Optimal speed and accuracy of object detection,” arXiv preprint arXiv:2004.10934, 2020.

[8] D. S. Hui, E. I. Azhar, T. A. Madani, F. Ntoumi, R. Kock, O. Dar, G. Ippolito, T. D. Mchugh, Z. A. Memish, C. Drosten et al., “The continuing 2019-ncov epidemic threat of novel coronaviruses to global health—the latest 2019 novel coronavirus outbreak in Wuhan, China,” International Journal of Infectious Diseases, vol 91, pp. 264–266, 2020.

[9] M. Greenstone and V. Nigam, “Does social distancing matter?” University of Chicago, Becker Friedman Institute for Economics Working Paper, no. 2020-26, 2020.

[10] Z. Zou, Z. Shi, Y. Guo, and J. Ye, “Object detection in 20 years: A survey,” arXiv preprint arXiv:1905.05055, 2019
.

[11] Z.-Q. Zhao, P. Zheng, S.-t. Xu, and X. Wu, “Object detection with deep learning: A review,” IEEE transactions on neural networks and learning systems, vol. 30, no. 11, pp. 3212–3232, 2019.

[12] R. Girshick, J. Donahue, T. Darrell, and J. Malik, “Rich feature hierarchies for accurate object detection and semantic segmentation,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2014, pp. 580–587.

[13] J. Redmon and A. Farhadi, “Yolov3: An incremental improvement,” arXiv preprint arXiv:1804.02767, 2018.

[14] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. C. Berg, “Ssd: Single shot multibox detector,” in European conference on computer vision. Springer, 2016, pp. 21–37.

[15] M. Tan, R. Pang, and Q. V. Le, “Efficient Det: Scalable and efficient object detection,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 10 781–10 790.

[16] H. Law and J. Deng, “Cornernet: Detecting objects as paired keypoints,” in Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 734–750.

[17] Z. Tian, C. Shen, H. Chen, and T. He, “Fcos: Fully convolutional one-stage object detection,” in Proceedings of the IEEE international conference on computer vision, 2019, pp.9627–9636.

[18] M. Everingham, L. Van Gool, C. K. Williams, J. Winn, and A. Zisserman, “The pascal visual object classes (voc) challenge,” International journal of computer vision, vol. 88, no. 2, pp. 303–338, 2010.

[19] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollar, and C. L. Zitnick, “Microsoft coco: Common objects in context,” in European conference on computer vision. Springer, 2014, pp. 740–755.

[20] LandingAI, Landing AI Creates an AI Tool to Help Customers Monitor Social Distancing in the Workplace, 2020

[21] P. Khandelwal, A. Khandelwal, and S. Agarwal, “Using computer vision to enhance safety of workforce in manufacturing in a post covid world,” arXiv preprint arXiv:2005.05287, 2020

[22] https://towardsdatascience.com/non-maximum-suppression-nms-93ce178e177c

[23] https://medium.com/ibm-data-ai/faster-r-cnn-vs-yolo-vs-ssd-object-detection-algorithms-18badb0e02dc

[24] Srivastava, S., Divekar, A.V., Anilkumar, C. et al. Comparative analysis of deep learning image detection algorithms. J Big Data 8, 66 (2021). https://doi.org/10.1186/s40537-021-00434-w

[25] World Health Organization. Coronavirus disease 2019 (COVID-19): situation report. 156 (2020). www.who.int/docs/default-source/coronaviruse/situation-reports/20200624-covid-19-sitrep-156.pdf?sfvrsn=af42e480_2 Google Scholar

[26] Geethapriya. S, N. Duraimurugan, S.P. Chokkalingam,”Real-Time Object Detection with Yolo”,International Journal of Engineering and Advanced Technology vol.-8, Issue-3S

[27] S. Guennouni, A. Ahaitouf and A. Mansouri, "Multiple object detection using OpenCV on an embedded platform," 2014 Third IEEE International Colloquium in Information Science and Technology (CIST), Tetouan, Morocco, 2014, pp. 374-377, doi: 10.1109/CIST.2014.7016649
.

[28] Edouard Mathieu, Hannah Ritchie, Lucas Rodés-Guirao, Cameron Appel, Charlie Giattino, Joe Hasell, Bobbie Macdonald, Saloni Dattani,

Diana Beltekian, Esteban Ortiz-Ospina and Max Roser (2020) - "Coronavirus Pandemic (COVID-19)". Published online at OurWorldInData.org. Retrieved from: 'https://ourworldindata.org/coronavirus' [Online Resource]

[29] https://cv-tricks.com/object-detection/faster-r-cnn-yolo-ssd/