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REAL-TIME SOCIAL DISTANCING AND MASK DETECTION

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Abstract :The paper presents a methodology for social distancing detection using deep learning to evaluate the distance between people to mitigate the impact of this coronavirus pandemic. The detection tool was developed to alert people to maintain a safe distance with each other by evaluating a video feed. The video frame from the camera was used as input, and the open-source object detection pre-trained model based on the YOLOv3 algorithm was employed for pedestrian detection. Later, the video frame was transformed into a top-down view for distance measurement from the 2D plane. The distance between people can be estimated and any noncompliant pair of people in the display will be indicated with a red frame and red line. The proposed method was validated on a pre-recorded video of pedestrians walking on the street. In addition to the social distancing face mask detector also integrated. The face mask detector model is constructed using CNN and the accuracy of the face mask detector is 90%. The result shows that the proposed method is able to determine the social distancing measures between multiple people in the video. The developed technique can be further developed as a detection tool in real time application.

Keywords : *Python,OpenCV,YOLOv5, CNN.*

I.INTRODUCTION

When the novel coronavirus (Covid-19) pandemic emerged, the spread of the virus left the public anxious if they did not have any effective cure. The World Health Organization (WHO) has declared Covid-19 as a pandemic due to the increase in the number of cases reported around the world [1]. To contain the pandemic, many countries have implemented a lockdown where the government forces the citizens to stay at home during this critical period. The public health bodies such as the Centers for Disease Control and Prevention (CDC) had to make it clear that the most effective way to slow down the spread of Covid-19 is by avoiding close contact with other people [2]. To flatten the curve on the Covid-19 pandemic, the citizens around the world are practising physical distancing. To implement social distancing, group activities and congregations such as travel, meetings, gatherings, workshops, praying had been banned during the quarantine period. The people are encouraged to use phone and email to manage and conduct events as much as possible to minimise the person-to-person contact. To further contain the spread of the virus, people are also informed to perform hygiene measures such as frequently washing hands, wearing masks and avoiding close contact with people who are ill. However, there is a difference between knowing what to do to reduce the transmission of the virus and putting them into practice. The world has not yet fully recovered from this pandemic and the vaccine that can effectively treat Covid-19 is yet to be discovered. However, to reduce the impact of the pandemic on the country‟s economy, several governments have allowed a limited number of economic activities to be resumed once the number of new cases of Covid-10 has dropped below a certain level. As these countries cautiously restart their economic activities, concerns have emerged regarding workplace safety in the new post-Covid-19 environment. To reduce the possibility of infection, it is advised that people should avoid any person-to-person contact such as shaking hands and they should maintain a distance of at least 1 metre from each other. In Malaysia, the Ministry of Health Malaysia (MOHM) has recommended several disease prevention measures for workplaces, individuals, and families at home, schools, childcare centres, and senior living facilities [3]. These measures include implementing social distancing measures, increasing physical space between workers at the workplace, staggering work schedules, decreasing social contacts in the workplace, limiting large work-related gatherings, limiting non-essential work travel, performing regular health checks of staff and visitors entering buildings, reducing physical activities especially for organisations that have staff in the high-risk category, and conducting company events or activities online.

Individuals, communities, businesses, and healthcare organisations are all part of a community with their responsibility to mitigate the spread of the Covid-19 disease. In reducing the impact of this coronavirus pandemic, practising social distancing and self-isolation have been deemed as the most effective ways to break the chain of infections after restarting the economic activities. In fact, it has been observed that there are many people who are ignoring public health measures, especially with respect to social distancing. It is understandable that given the people‟s excitement to start working again, they sometimes tend to forget or neglect the implementation of social distancing. Hence, this work aims to facilitate the enforcement of social distancing by providing automated detection of social distance violation in workplaces and public areas using a deep learning model. In the area of machine learning and computer vision, there are different methods that can be used for object detection. These methods can also be applied to detect the social distance between people. The following points summarise the main components of this approach: a. Deep learning has gained more attention in object detection and was used for human detection purposes. b. Develop a social distancing detection tool that can detect the distance between people to keep safe. c. Evaluation of the classification results by analysing real-time video streams from the camera.

II.LITERATURE SURVEY

D.T. Nguyen, et.al., The problem of human detection is to automatically locate people in an image or video sequence and has been actively researched in the past decade. This paper aims to provide a comprehensive survey on the recent development and challenges of human detection. Different from previous surveys, this survey is organised in the thread of human object descriptors. This approach has advantages in providing a thorough analysis of the state-of-the-art human detection methods and a guide to the selection of appropriate methods in practical applications. In addition, challenges such as occlusion and real-time human detection are analysed. The commonly used evaluation of human detection methods such as the datasets, tools, and performance measures are presented and future research directions are highlighted.

Mustafa Alghali Elsaid Muhammed, et. al., Deep Convolutional Neural Networks (CNNs) have recently demonstrated the state-of-the-art classification performance on ImageNet Large Scale Visual Recognition Challenge (ILSVRC) since 2012, yet there is relatively no clear understanding of the reasons behind their outstanding performance, or how they might be improved, In this paper we present a novel benchmarking of multiple state-of-the-art deep CNN architectures by providing an analysis of important performance metrics: speed, memory consumption, and network parameters utilisation. Key findings are: (1) fully connected layers are of a high cost on speed and memory consumption compared to the sparsely connected layers; (2) the depth and the performance of an architecture are in a nonlinear relationship and constrained by layers transformation types; (3) 1×1 convolutions are an efficient way to reduce dimensionality and pooling features; (4) addition units as in residual and densely connected networks accelerate the backpropagation time by distributing the gradients through the graph, we believe our set of benchmarks are a step towards better realisation of the best architectural design choices of Deep CNNs.

Jia Deng, et. al., The explosion of image data on the Internet has the potential to foster more sophisticated and robust models and algorithms to index, retrieve, organise and interact with images and multimedia data. But exactly how such data can be harnessed and organised remains a critical problem. We introduce here a new database called “ImageNet”, a large-scale ontology of images built upon the backbone of the WordNet structure. ImageNet aims to populate the majority of the 80,000 synsets of WordNet with an average of 500–1000 clean and full resolution images. This will result in tens of millions of annotated images organised by the semantic hierarchy of WordNet. This paper offers a detailed analysis of ImageNet in its current state: 12 subtrees with 5247 synsets and 3.2 million images in total. We show that ImageNet is much larger in scale and diversity and much more accurate than the current image datasets. Constructing such a large-scale database is a challenging task. We describe the data collection scheme with Amazon Mechanical Turk. Lastly, we illustrate the usefulness of ImageNet through three simple applications in object recognition, image classification and automatic object clustering. We hope that the scale, accuracy, diversity and hierarchical structure of ImageNet can offer unparalleled opportunities to researchers in the computer vision community and beyond.

K. Simonyan, A. Zisserman et. al., In this work we investigate the effect of the convolutional network depth on its accuracy in the large-scale image recognition setting. Our main contribution is a thorough evaluation of networks of increasing depth, which shows that a significant improvement on the prior-art configurations can be achieved by pushing the depth to 16-19 weight layers. These findings were the basis of our ImageNet Challenge 2014 submission, where our team secured the first and the second places in the localisation and classification tracks respectively.

J. Redmon, et. al. Studied present YOLO, a new approach to object detection. Prior work on object detection repurposes classifiers to perform detection. Instead, we frame object detection as a regression problem to spatially separated bounding boxes and associated class probabilities. A single neural network predicts bounding boxes and class probabilities directly from full images in one evaluation. Since the whole detection pipeline is a single network, it can be optimised end-to-end directly on detection performance. Our unified architecture is extremely fast. Our base YOLO model processes images in real-time at 45 frames per second. A smaller version of the network, Fast YOLO, processes an astounding 155 frames per second while still achieving double the mAP of other real-time detectors. Compared to state-of-the-art detection systems, YOLO makes more localization errors but is less likely to predict false positives in the background. Finally, YOLO learns very general representations of objects. It outperforms other detection methods, including DPM and R-CNN, when generalising from natural images to other domains like artwork.

IIIEXISTING SYSTEM

YOLOv3 uses Darknet Architecture and has 53 layers trained with the ImageNet dataset . YOLOv3 uses residual connections and upsampling. The detection is performed at three different scales. It is more efficient in detecting smaller objects however; it has a longer processing time as compared to the previous versions. The YOLOv4 architecture is composed of CSPDarknet53 as a backbone, spatial pyramid pooling additional module, PANet path-aggregation neck and YOLOv3 head. Existing models are designed using above models.

Drawbacks

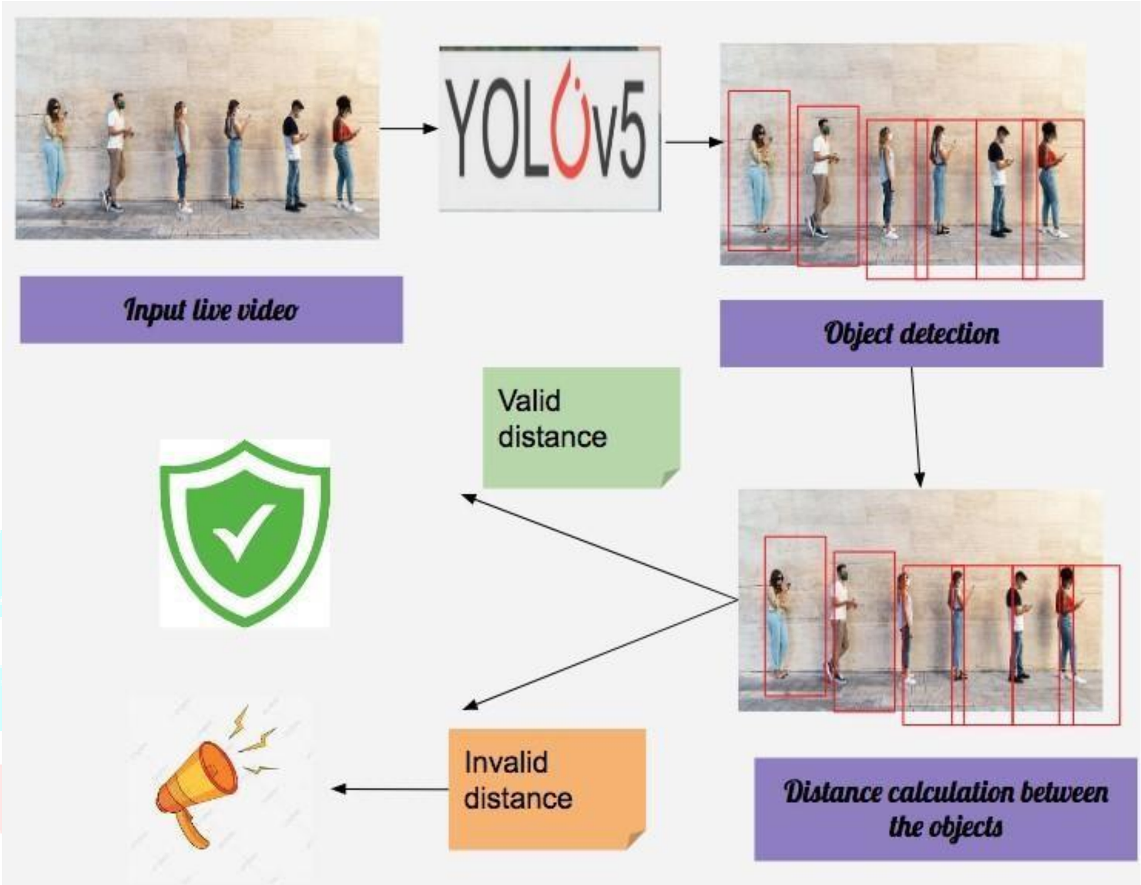
- Time taken for training time of existing models is higher than the YOLOv5.

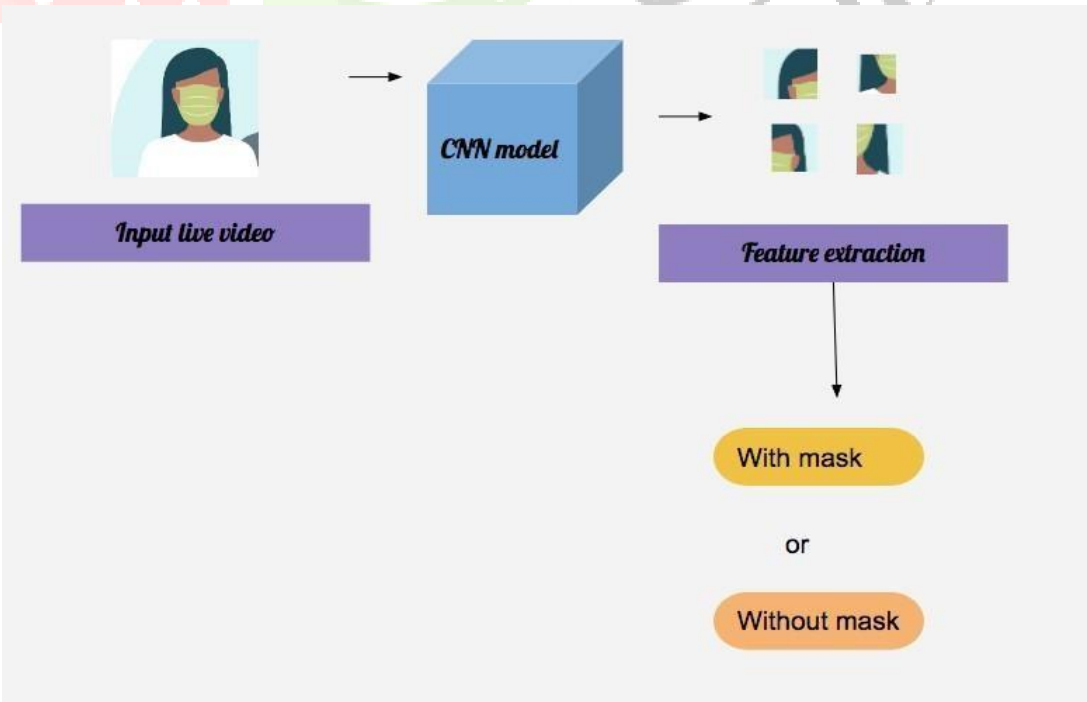
IV.PROPOSED SYSTEM

The YOLOv5 model consists of Focus structure and CSP network as the backbone. The neck is composed of SPP block and PANet. It has a YOLOv3 head using GIoU-loss.

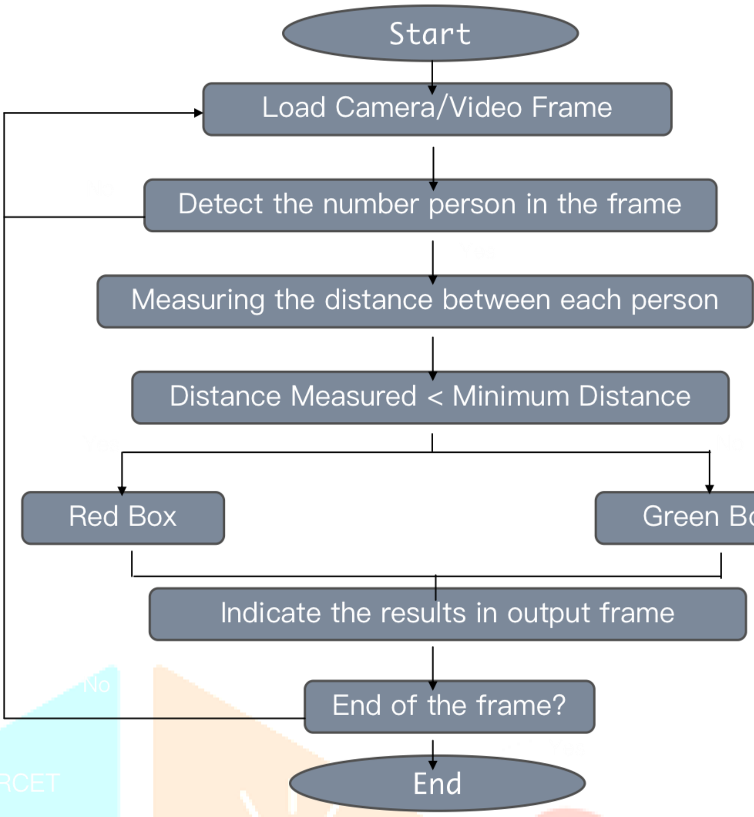
YOLOv5 is written in Python programming language.

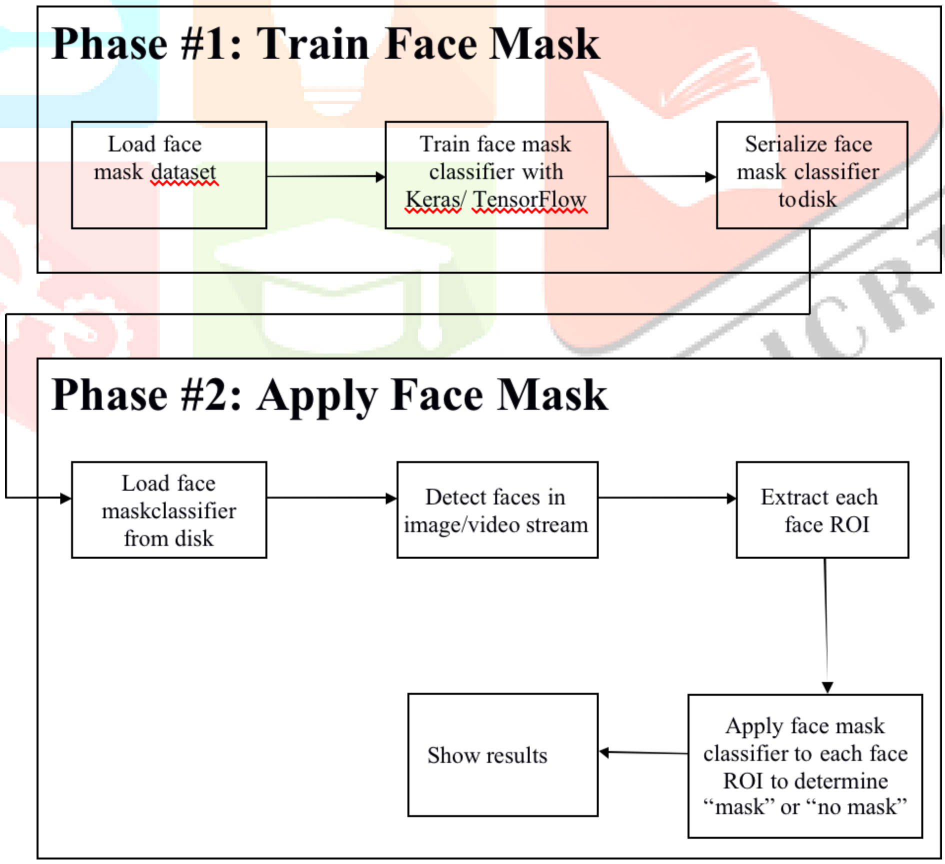
V.ARCHITECTUREDIAGRAM





VI FLOW CHART





VII. FUNCTIONAL REQUIREMENTS

In the implementation there are 3 modules mainly.

Social distance detector

- In this module user can check the valid „distance" for social distancing through
  - Image
  - Live video
- While uploading the image user can choose any random image with the people the social distancing detector will find the valid distance between the people in the image
- In the same manner a live video of 3 or more people in the standing position gives the valid the distance between the people
- As per the covid guidelines the valid distance between two people is 2 arm"s length this can be tuned according to the need.

Face mask detector:

- Face mask detector model is constructed using CNN model
- In this module given Live video of the single person face will be categorised into with mask and without mask.

Non functional requirements:

Compatibility: To implement this we need basic equipment like a laptop with any operating system required. Preferably windows operating system is required.

Maintainability + Manageability: The system design is simple it does not require any extra effort to maintain the system. **Usability :**Due to less maintenance it can be easily implemented in any place or any private crowd areas

VIII.HARDWARE AND SOFTWARE REQUIREMENT

Hardware Requirement

Processor	Intel i5,
Ram	8 GB
Hard Disk	1 TB

Software Requirements

Programming language	Python 3.7
IDE	Pycharm

IX.ADVANTAGES

- Training time for the proposed algorithm is less compared to the existing algorithms
- Accuracy of the algorithm is higher than the existing algorithms.

X. CONCLUSION AND FUTURE WORK

A methodology of social distancing detection tool using a deep learning model is proposed. By using computer vision, the distance between people can be estimated and any noncompliant pair of people will be indicated with a red frame and a red line. The proposed method was validated using a video showing pedestrians walking on a street. The visualisation results showed that the proposed method is capable of determining the social distancing measures between people which can be further developed for use in other environments such as office, restaurant, and school. Furthermore, the work can be further improved by optimising the pedestrian detection algorithm, integrating other detection algorithms such as mask detection and human body temperature detection, improving the computing power of the hardware, and calibrating the camera perspective view.

REFERENCES

[1] Centers for Disease Control (CDC). Implementation of Mitigation Strategies for Communities with Local COVID-19 [Online]. Available at: https://www.who.int/emergencies/diseases/novel-coronavirus-2019 (Accessed 8 May 2020).

[2] Centers for Disease Control (CDC). Implementation of Mitigation Strategies for Communities with Local COVID-19 Transmission [Online]. Available at https://www.cdc.gov/coronavirus/2019-ncov/downloads/community-mitigationstrategy.pdf (Accessed 8 May 2020).

[3] Ministry of Health Malaysia (MOHM) Official Portal. COVID-19 (Guidelines) [Online]. Available at https://www.moh.gov.my/index.php/pages/view/2019-ncov-wuhanguidelines (Accessed 8 May 2020).

[4] D.T. Nguyen, W. Li, P.O. Ogunbona, "Human detection from images and videos: A survey", Pattern Recognition, 51:14875, 2016.

[5] A. Krizhevsky, I. Sutskever, G.E. Hinton, "Imagenet classification with deep convolutional neural networks", In Advances in neural information processing systems, pp. 1097-1105, 2012.

[6] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, L. Fei-Fei, "ImageNet: A Large-Scale Hierarchical Image Database", In Computer Vision and Pattern Recognition, 2009.

[7] K. Simonyan, A. Zisserman, "Very deep convolutional networks for large-scale image recognition", arXiv preprint arXiv:1409.1556, 2014.

[8] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, Z. Wojna, “Rethinking the inception architecture for computer vision”, In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 2818- 2826, 2016.

[9] K. He, X. Zhang, S. Ren, J. Sun, “Deep residual learning for image recognition”, InProceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778, 2016.

[10] R. Girshick, J. Donahue, T. Darrell, J. Malik. "Rich feature hierarchies for accurate object detection and semantic segmentation." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 580-587. 2014.

[11] J. Redmon, S. Divvala, R. Girshick, A. Farhadi, “You only look once: Unified, real-time object detection”, In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 779-788. 2016.

[12] Landing AI Creates an AI Tool to Help Customers Monitor Social Distancing in the Workplace [Onlive]. Available at https://landing.ai/landing-ai-creates-an-ai-tool-to-help-customersmonitor-social-distancing-inthe-workplace/ (Access on 4 May 2020).

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