

Ministry of Higher Education  
And Scientific Research  
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College of Science  
Department of Computer Science



# **A Developed Model for Social Distancing under the Corona Pandemic using YOLOv5 Algorithm**

**A Thesis Submitted to the Department of Computer Science \ College  
of the Science \ University of Diyala in a Partial Fulfillment of the  
Requirements for the Degree of Master's in Computer Science**

**By**

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بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

قَالَ رَبِّ اجْعَلْ لِي صِدْقًا وَسِيرًا  
مُبِينًا لِي لِيُؤْتِيَنِي مِنْهُ حَقًّا  
وَلَا حَوْلَ لِي فِيهِ وَمَا أَكْفُرُ

صِدْقًا وَاللَّهُ الْعَظِيمُ

سورة طه الايات (25-28)

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*Hiyam Hashem Saeed*

## *Dedication To...*

*To her. The soul that brings me strength whenever. I feel to whenever. I need kindness. The present that has not gone away from me for a moment (my mother).*

*To my tent (my father).*

*To the soul of my martyr brother (Muthafer).*

*To who stood by my side to the end (my affectionate husband).*

*To my brothers and sisters*

*To my daughters.*

*All our distinguished teachers are those who paved the way for our science and knowledge.*

*To all My Friends.*

*I produce this work with all my love...*



*Hiyam Hashem Saeed*

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This is to certify that this thesis entitled “**A Developed Model for Social Distancing under the Corona Pandemic using YOLOv5 Algorithm**” was prepared by **Hiyam Hashem Saeed** under my linguistic supervision. It was amended to meet the style of English language.

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## **Abstract**

Coronavirus COVID-19 causes severe respiratory illness. It was discovered in Wuhan city, China, in December 2019 [5]. A continuous pandemic has resulted in a massive number of infections and deaths. Close contact between humans is currently the primary means of propagating the coronavirus, with the succession of corona waves and the arrival of the fifth wave at the time of writing this thesis. The most effective and unique method for preventing the transmission of coronavirus disease is to limit physical contact with infected persons.

World Health Organization (WHO) suggests social distancing as a solution. Most governments and national health authorities have mandated a 6-foot physical distance as a safety precaution. It is urgently needed to have a crowd monitoring system that can detect people's presence, identify the crowd, and issue social distancing warnings.

In this study, a model has suggested a methodology for detecting social distancing among individuals. This model consists of personal localization and detection using the You Only Look Once version5 (YOLOv5) and evaluating the Microsoft Common Objects in Context (MS-COCO) dataset. After people detect, Euclidean distance is used to determine the pair-wise distance between people in an image. The ability of this model to detect a social distance between persons has been demonstrated using a variety of test videos in real-time by IP camera or offline (saved videos or YouTube). Supporting the proposed system by sending alert messages in case of violation distance of the specified threshold distances between people and can validate the social distance model by using 'Video Dataset for COVID-19 Social Distancing and Human Detection Validation'.

The suggested model has two results stages, and the first is for the YOLOv5 object detection, where it has trained to detect only people. The

model training takes about 8 seconds to complete each epoch, and with 150 epochs, splitting the COCO dataset by 10% testing, 10% validation, and 80 % training. Accuracy was about 99.5%, F1 was about 99.84, FPS was 140, reference time was 20 ms, and validation of YOLOv5 training resulted in a 100 % true positive and 100 % false positive rate. The YOLOv5 yields equivalent results to the entire YOLOv3 model while requiring around 75 % fewer procedures.

YOLOv5 has the same benefits and a nearly identical architecture as YOLOv4. The execution of YOLOv5 has been finished in Pytorch, along with other projects that have used the DarkNet technology.

The second result for distance measurements showed the error ratio (-0.05 to 0.12) in testing the distance accuracy of the One\_Meter\_Distance video and the error ratio between (-0.04 to 0.04) in testing the distance accuracy of the Two\_Meter\_Distance video.

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## List of Abbreviations

Abbreviations	Meaning
AI	Artificial Intelligence
ANN	Artificial Neural Network
AP	Average Precision
CCTV	Closed-Circuit Television
CNN	Convolutional Neural Network
COVID19	Coronavirus Disease 2019
CPU	Central Processing Unit
CSP	Cross-Stage Partial
DVR	Digital Video Recorder

Faster-RCNN	Faster Region Convolution Neural Network
FN	False Negative
FP	False Positive
FPN	Feature Pyramid Network
FPS	Frames Per Second
GIoU	Generalized Intersection over Union
IoU	Intersection Over Union
mAP	Mean Average Precision
MS-COCO	Microsoft Common Objects in Context
NMS	Non-Maximum Suppression
OpenCV	Open-Source Computer Vision Library
PANet	Path Aggregation Network
RTSP	Real Time Streaming Protocol
SGD	Stochastic Gradient Descent
SPP	Spatial Pyramid Pooling
SSD	Single-Shot Detector
TN	True Negative
TP	True Positive
WHO	World Health Organization
YOLO	You Only Look Once
Yaml	Yet another markup language

## **CHAPTER ONE**

# **General Introduction**

# Chapter One

## Introduction

### 1.1 Overview

Social Distancing is one of the most efficient methods to prevent the transmission of the virus, which is transmitted by airborne droplets [1].

The late 2019 global outbreak of an unidentified disease was one of the most significant concerns facing the planet in the 21st century. The disease was previously unknown, but specialists determined that its symptoms were identical to those of influenza and Coronavirus. Following laboratory research and experimentation with Polymerase Chain Reaction (PCR) tests, this hidden infection classifies as COVID-19 according to the advice of the World Health Organization (WHO). This disease spreads rapidly over country borders, suffering catastrophic health consequences, economic disasters, and the welfare of the worldwide population [2].

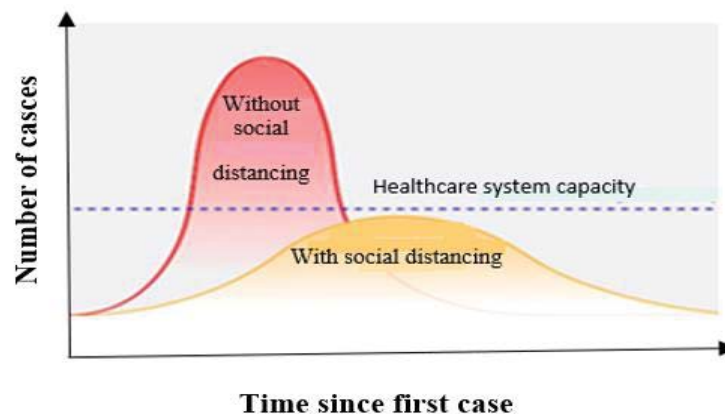
Numerous medical authorities suggested that social distancing is the most effective method for stopping the spreading of the contagious virus [3]. This pandemic altered the world's lifestyle, transforming it into an electronic one. In light of this notification, security personnel may take the necessary precautions [4] [5].

This chapter will present an overview and background of social distancing. Related work of researchers, problem statement, challenges, the aim, and the objective of thesis.

## 1.2 Background of Social Distancing

World Health Organization (WHO) determined that social distancing was the most efficient way to overcome viral infections. Several researchers conducted a timely study on the effect of social distance on reducing the propagation of the COVID-19 pandemic and reported extremely optimistic results, supporting WHO and CDC recommendations [5].

These organizations have proposed many preventative measures to limit the spread of coronavirus. Social distancing [6] is one of the best ways to prevent infection under the present circumstances by using this method. Everyone should maintain a distance of at least 6 feet to maintain social distance. As demonstrated by research [7], Figure (1.1) depicts the measurement curve for individuals who observe social distancing and have a lower COVID-19 infection rate than those who do not adhere to the WHO protocol [8].



**Figure (1.1):** With and without the obligation of social distancing [8].

According to WHO, the coronavirus is transmitted from person to person via minute oral and nasal droplets [9]. Figure (1.2) depicts the potential propagation of the COVID-19 virus in thirty days of absent social distancing [10].



**Figure (1.2):** The ability of the virus to propagate without social distancing [10]

### 1.3 Related works

It is known that the coronavirus arose at the end of 2019 and up to now. Numerous studies and research use Deep learning that contributed to finding methods to avert this pandemic that appeared during this period.

Many researchers have used social distancing and object detection to contribute to finding solutions to this viral pandemic, as reviewed:

- **N.Punn et al. 2020 [11]:** the design is based on automated social distancing surveillance systems using video footage. The structure of the system uses YOLOv3 as an object detection model. Separate people within the backdrop and the deepsort technique to track recognized individuals that use boundary boxes and IDs. The findings of YOLOv3 were comparable to those of other famous state-of-the-art models, such as region-based CNN and single-shot detector (SSD), based on mean average precision (mAP) and frames per second (FPS), with loss values specified for object detection and location. PASCAL-VOC and MS-COCO datasets use. YOLO v3 and Deepsort showed the results, and this calculated the social distance in actual time by balancing mAP and FPS scores, where mAP was 84.6% and 23 FPS.

- **Harith et al .2020 [9]:** social distance monitoring was employed to restrict human contact between individuals. This work focused on recognizing

individuals in an exciting area by utilizing MobileNet's SSD detection model and OpenCV- based image recognition and using the MS-COCO dataset. The technology may detect people in prohibited locations and issue warnings if necessary. Accuracy rates of 56.5% to 68.5% attain using distance tracking technology in challenging outdoors. In comparison, indoor testing in a controlled environment yielded a perfect score of 100 percent accuracy. The segmented ROI safety breach warning function achieved 95.8 percent to one hundred percent accuracy for all input videos.

- **P.Somaldo et al .2020** [12]: presented a drone that can localize, maneuver, and identify humans, along with crowd identifiers and social distance alerts. They employ YOLOv3 to identify individuals and propose an effective social distance monitor. Using the Robot Operating System created a road segmentation and gazebo simulation on the IRIS PX4 drone. Additionally, successful person and crowd detection demonstrations were made using the suggested system in varied crowd densities. The accuracy of this system in detecting crowds was approximately 90%, and it was expected to be easily deployed on actual drone hardware and tested in real scenarios.

- **M. Rezaei et al .2020** [8]: created a Deep Neural Network (DNN) model that combines computer vision and YOLOv4 for automatically detecting persons in crowds using CCTV security cameras. Their methodology improves people detection and social distance monitoring. MS-COCO and Google Open Image datasets were used to train the model. The approach outperformed three state-of-the-art algorithms on the 150,000-person Oxford Town Centre dataset. The examination was completed in demanding settings, including occlusion, partial vision, and lighting fluctuations, with 99.8% accuracy and 24.1 FPS real-time speed. It provides an infection risk assessment technique by statistically analyzing moving trajectories and social distancing breaches.

- **R. Magoo et al .2021** [10]: suggested a method that uses Key point regression and object detection model for YOLOv3 to determine the essential feature points. In addition, the item's bounding boxes are received when a large crowd is discovered, and red boxes are displayed if the social distance is breached. According to these results, the suggested approach was more efficient than the already available options in terms of inference time was 25 MS, the frame rate was 51 based on empirical testing using real-time data, and the mAP was 51%.

- **Ben Abdel Ouahab et al.2021** [13]: proposed an intelligent method of monitoring in which a prototype detects people to guarantee that social distance is respected, measuring the distance between them and producing audible warnings. The prototype for intelligent surveillance is developed on the Raspberry Pi with Camera Pi. Next, they conduct comparative research on object detection models that have been pre-trained. Using the Raspberry Pi with minimal computational resources, SSD-MobileNet yields the most pleasing results. Although implementing a CNN-based model on the Raspberry Pi is challenging, they achieve real-time object detection and a distance assessment rate of 1.1 FPS.

- **Ahmed et al .2021** [14]: as a preventive measure, introduced a social distancing framework built on the architecture of deep learning that maintains, monitors, manages, and reduces the physical connection between people in a real-time top-view environment. Faster-RCNN was utilized to recognize humans in images. The architecture is trained using the data set for the top view of humans. Experiments were conducted using a variety of test photos. There are strong indications that the framework can accurately measure the social distance between individuals; the transfer learning technique enhances the framework's overall performance by reaching a 96 % accuracy and a 0.6% False Positive Rate.



- **M. Aquib and D. Kumar.2021** [15]: presented a framework-based method for tracking individuals to keep tabs on the physical distance between people. Investigating the use of a CNN-based detection algorithm to detect human existence. The output of the object detector is the distance between every couple of observed persons. This method of the social distance algorithm highlights in red those individuals who are approaching an acceptable proximity threshold. Using their suggested social distance system and CNN-based object detectors, the researchers found promising findings in their study of social distancing in public areas. The two models' overall performance reached 97 % accuracy for model 1 and 98.5% for model 2.

- **S. Jethani et al. 2021** [16]: described a plan to prevent the spread of disease by monitoring distance from others. Utilizing a combination of cutting-edge detection algorithms such as SSD, YOLOv4, and Faster-RCNN with pedestrian datasets. They calculated the distance between two individuals in a video and decided whether the social distancing standard was observed. Therefore, the method applies to CCTVs, UAVs, and other monitoring systems. Fast technological progress has resulted in increasingly exact precise values. The algorithms' overall performance of mAP for SSD is 48%, YOLO v4 is 87%, and Faster- RCNN is 68%.

- **S. Saponara et al .2021** [17]: proposed thermal imaging and AI to socially distance people, and using the YOLOv2 algorithm, a one-of-a-kind deep learning detection technique was developed to recognize and identify people indoors and out. The approach seeks to minimize COVID-19 viral spread by considering social distancing criteria. The training uses two thermal camera datasets. The Ground Truth Labeler labels people in images. An embedded camera system employs this technique (Jetson Nano). A variety of cameras can watch people by a variety of cameras as part of a distributed surveillance system. The results suggested that the proposed method is suitable

for person detection. In smart cities, body temperature and social distance classification are used. The performance in Dataset I was 95.6% accuracy, 95% mAP, and 96% recall, and by using dataset II, the performance reached 94.5% accuracy, 94% mAP, and 94.5% recall.

- **N. Hossein et al. 2021 [18]:** assessed the potential of repurposing Sensors and environmental sensors for monitoring social distance and estimating the risk of disease transmission. Before the 2017-2018 epidemic, they collected 410 days of CO2 and passive infrared (PIR) motion sensor data from a shared intelligent space. They show how these sensors can measure and assess space occupancy. They also utilize air quality to estimate transmission hazards. Based on their investigation, they offer advice on improving issue areas to be more socially distant. The model had a test data accuracy of 97.28 % and a validation data accuracy of 97.58 %.

- **N. Darapaneniet al. 2022 [19]:** created YOLOv5 based on social distance monitoring with an overhead view. They constructed a custom-defined model YOLOv5 modified CSP and tested MS-COCO and Visdrone datasets with transfer learning and without it. After 300 epochs of training on the MS-COCO dataset, the modified bottleneck CSP achieves 81.7% accuracy without transfer learning; in contrast, the YOLOv5 model achieves 80.1% accuracy with transfer learning. The improved bottleneck CSP model improves accuracy. Transfer learning can obtain up to 56.5% accuracy for specific classes and 40% for individuals and pedestrians with 30 epochs of transfer learning using the YOLOv5s model. The modified bottleneck CSP performs marginally better than the default model, with up to 58.1% accuracy for specific classes and 40.4% for people and pedestrians. The following Table (1.1) summarizes the related works.

**Table (1.1): Summary of related works**

Year and no. of references	Methodology and gaps	Performance	Dataset
2020 [11]	<ul style="list-style-type: none"> <li>Used YOLO v3 and the Deepsort approach in real-time.</li> <li>A higher number of false positives may raise discomfort and panic among people being observed.</li> </ul>	mAP 84.6% FPS 23	MS-COCO dataset
2020 [9]	<ul style="list-style-type: none"> <li>Processing images using the OpenCV library and MobileNet's Single Shot Multibox Detector (SSD) model.</li> <li>Not focused on term object detection.</li> </ul>	Accuracy 95.8%	MS-COCO dataset
2020 [12]	<ul style="list-style-type: none"> <li>They employ the YOLO-v3 algorithm to detect persons using Robot Operating System (ROS), and Gazebo simulation results use the IRIS PX4 drone.</li> <li>Not add localization and mapping if the drone explores new locations.</li> </ul>	Accuracy 90%	Manually collected dataset
2020 [8]	<ul style="list-style-type: none"> <li>They developed a Deep Neural Network (DNN) model based on computer vision and YOLOv4, an updated inverse perspective mapping (IPM) with the SORT tracking algorithm and CCTV security cameras.</li> <li>Frame per second was 24.1, which to the model, indicates that it takes more time to implement.</li> </ul>	Accuracy 99.8% FPS 24.1	MS-COCO Google Open Image datasets
2021 [10]	<ul style="list-style-type: none"> <li>Used YOLOv3 over real-time by CCTV Surveillance camera.</li> <li>It tests the model only in containment zones, not testing the complete system to check up on the big crowd to monitor the general population.</li> </ul>	mAP 51%	Oxford Town Center data
2021 [13]	<ul style="list-style-type: none"> <li>They conducted a comparative analysis of a model pre-trained for detecting the presence of an object using Raspberry Pi and Camera pi.</li> </ul>	FPS 1.1	PASCAL (VOC0712) MS-COCO

	<ul style="list-style-type: none"> <li>Raspberry Pi is limited in terms of computing resources. And deep learning models do not take into consideration 3D situations.</li> </ul>		datasets
2021 [14]	<ul style="list-style-type: none"> <li>They used Faster-RCNN for person detection in the photos and transfer learning approaches to enhance the framework's overall efficiency and use IP cameras.</li> <li>Faster RCNN is a two-stage detector that localizes before classifying. This method is slower than one-stage detectors, such as YOLO, which perform both functions in a single stage.</li> </ul>	Accuracy 96 % False Positive Rate 0.6%.	MS-COCO dataset
2021 [15]	<ul style="list-style-type: none"> <li>They use two successive CNN models to detect a person's location in an image and a CCTV camera.</li> <li>There is no indication of the algorithms that were employed.</li> </ul>	<b>Model 1</b> Accuracy 97% <b>Model 2</b> Accuracy 98.5%.	Manually collected dataset
2021 [16]	<ul style="list-style-type: none"> <li>Combining sophisticated detection algorithms such as YOLO v4 and Faster-RCNN with pedestrian datasets, SSD could address the limitations of this system and enhance its ability to distinguish between people and uncrewed aerial vehicles (UAV) at high altitudes by using CCTVs, UAVs, and any other surveillance system.</li> <li>They have to enter the four spots for the distance calculation.</li> </ul>	<b>mAP</b> for SSD 48%, YOLOv4 87%, and Faster-RCNN 68%.	MS-COCO dataset
2021 [17]	<ul style="list-style-type: none"> <li>The YOLO v2 algorithm and technique have been implemented in embeddable hardware at a minimal cost (Jetson Nano) with a fixed camera and thermal camera.</li> <li>Not using experiment people detection.</li> </ul>	<b>DatasetI</b> Accuracy95.6% mAP 95 % Recall 96%  <b>DatasetII</b> Accuracy 94.5%  mAP 94 % Recall 94.5%.	<b>DatasetI</b> consists of 775 thermal images  <b>Dataset II</b> consists of 800 images

2021 [18]	<ul style="list-style-type: none"> <li>• They show how infrastructure-based sensors may discover trouble regions and how to make them more socially distant by using PIR sensors for movement and environmental CO2 sensors make up the sensor infrastructure.</li> <li>• Do not monitor solutions that can be used to support preventative health or countermeasures.</li> </ul>	<p>Test data accuracy 97.28 %</p> <p>Validation data accuracy 97.58 %</p>	Manually collected dataset
2022 [19]	<ul style="list-style-type: none"> <li>• YOLOV5 modified Cross-Stage Partial Network (CSP) with and without transfer learning and using a Drone surveillance system.</li> <li>• Only distributed video surveillance systems, drone surveillance systems, and similar surveillance systems may implement the proposed method.</li> </ul>	<p><b>1. MS-COCO</b></p> <p>81.7 % Without transfer learning.</p> <p>80.1% with transfer learning</p> <p><b>2. Visdrone</b></p> <p>up to 56.5% for certain classes</p> <p>-40% of people with transfer learning</p> <p>CSP is up to 58.1% for certain classes</p> <p>40.4% for pedestrians.</p>	<p>MS-COCO</p> <p>Visdrone datasets</p>

## 1.4 Problem Statement

1. Control the spread of Coronavirus, and it is challenging to implement the recommendation of WHO for social distancing without the application of artificial intelligence.
2. Using YOLOv5 enhanced by Cross Stage Partial Network (CSP).
3. Find a safe distance between individuals in real-time.

4. Find a safe distance between individuals offline.
5. Find solve the reliable and solid validation of the estimated distance between individuals in real-time video frame/s.

### 1.5 The objectives of the thesis

1. To reduce coronavirus propagation and economic effects by using AI. Using the YOLO v5 algorithm to localize and detect individuals in offline or real-time video frames. The Euclidean distance was used to calculate the distance between each pairwise centroid of the bounding box detected.
2. To implement monitoring social distancing in real-time by using an IP camera that supports RTSP.
3. The system sends an email to the responsible party to take precautionary measures if there is no safe distance.
4. To validate human detection and social distancing using ‘Video Dataset for COVID-19 Social Distancing and Human Detection Validation’.

### 1.6 Layout of Thesis

The other chapters in this thesis are as follows:

1. **Chapter two: Theoretical Background**, explains the methods used in this thesis.
2. **Chapter three: The Proposed System**, presents in detail the proposed algorithm used for social distancing.
3. **Chapter four: Experimental results, and evaluation**, presents the results of the proposed model implementation, analysis, and testing and evaluates these results.

4. **Chapter five: Conclusions, Challenges, and Suggestions for Future Work**, presents the conclusions drawn from this thesis and provides suggestions for expansion in the future.