EVALUATING THE NEW NORMAL

How Machine Learning can be used to evaluate social distancing regulations in public spaces

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Abstract. The ongoing impact of the Coronavirus pandemic has directed significant focus on maintaining health and safety through social distancing measures. Social distancing is maintained by reducing the rate of contact with other people and has proven to be effective in preventing the spread of the virus. Physical distancing is becoming the new normal and to ensure these measures are followed, social distancing patterns need to be monitored and evaluated. Applications of Artificial Intelligence and Machine Learning in day to day life are making it possible to address problems such as maintaining distancing using real-time data. This research project aims to create a Machine Learning-based monitoring system utilising real-time data to identify and evaluate social distancing, potentially allowing for better management of the distribution of people. The objective of this research is to create a system that can be implemented anywhere to detect social distancing quickly and efficiently within public spaces, allowing physical distancing patterns to be analysed and understood. This tool comprehends current societal issues, exploring how they intertwine with and affect the built environment, potentially leading to the re-evaluation of urban and spatial design post-Covid-19 through the study of socially distanced pedestrian movements.

Keywords. Machine Learning; Spatial Analysis; Social Distancing; Real-Time Data

1. Introduction

Since the first wave of the Coronavirus, the Australian Government has advised that members of the community stay 1.5 metres away from each other. This strategy has been put into practice to limit the spread of the virus and is the current requisite for physical distancing; Being the proven most effective way to stop the spread of disease (Australian Government Department of Health 2020). This distance is based on studies and prior knowledge of the spread of disease and is also a reasonable distance that allows society to continue going about their daily lives (P. Russo 2020). Before 2020, social distancing was not a common practice, despite being a term introduced by Edward Hall in 1963 (G. Szasz 2020); And whilst social distancing is not a new term, COVID-19 has brought this to the forefront of society. With the rise of the epidemic, this now seems to be the new normal, yet despite the scientific evidence and research supporting the effectiveness of social distancing, humans are creatures of habit and have proved that staying to requisite 1.5 metres is not always followed.

Through real-time data monitoring, social distancing patterns within public spaces can be evaluated, potentially leading to an increase in the number of people that stay the required distance apart whilst drawing awareness to the distribution of people within a space. This evaluation could in turn advocate for more efficient planning and design of public and semi-public spaces, providing data that addresses how a space is used and if it allows for social distancing to be practised reasonably and effectively. Monitoring and assessing these movement patterns would not only assist in preventing COVID-19, but social distancing has also been proven to help prevent other communal diseases, with studies showing that the Coronavirus distancing requirements have also helped stop the spread of the common flu (K. Blum 2020).

This research paper explores Machine Learning and how it can be employed in creating a social distancing detection tool in partnership with Pulse Software. Utilising an IP web camera phone application, cameras are placed in a fixed location where the approximated distance and depth is defined; this live video is then displayed on a web page developed using JavaScript. TensorFlow, an open-source platform for Machine Learning, is used to build and train the application to identify people. JavaScript is then used to find the centre points of people identified and calculate the distance between them. This live data can then be analysed to assist in decision making from rearranging an office space to rethinking urban infrastructure to promote an adaptable post-pandemic lifestyle.

Through the observation and evaluation of movement patterns, we can better plan and design for the future, promoting changes in Urban Design, widening pathways to ease pedestrian flow and Architectural and Computational design, creating spaces that are adaptable to post-Covid life.

This paper seeks to bridge the gap between Urban Planning and Computational Design fields through the implementation of AI through spatial analysis. By partaking in action and design research methodology, a cyclical workflow can be produced to create an iterative design approach. Through the support and feedback from industry partners, this paper aims to reach an outcome that is in line with current industry practices, testing the capabilities of current AI technologies to provide working solutions for real-time problems, in turn encouraging society to partake in the usage of computational design tools.

2. Research Aims

This research project aims to create an AI-based monitoring system employing real-time data to identify and evaluate social distancing. Real-time data monitoring can be applied to evaluate how effectively people stay the required 1.5 meters apart in public space, potentially allowing for better management of the distribution of people. The objective of this research is to design a system that can be implemented anywhere to detect social distancing quickly and efficiently within spaces, allowing physical distancing patterns to be interpreted and evaluated.

3. Research Question

Based on the issues outlined in the introduction and the derived aims, the question this project investigates is:

How can Machine Learning be utilised to spatially analyse real-time data to detect social distancing in public spaces?

4. Methodology

Action research takes real-world situations and holistically solves them, inferring that flexibility, involvement or change must result through problem-solving (Azhar et al. 2009). This research methodology focuses not on a 'thing' or 'object' but instead provides the 'how' and 'why' questions not always found through statistics or quantitative methods. Action research is a cyclical procedure (R. O'Brien 1998) consisting of four common characteristics: Action and change orientation, a problem focus, a systematic and sometimes iterative 'organic' process, and collaborations among participants (McNiff 2013).

Action research institutes diagnosing or identifying a problem (Foth 2006); This paper identifies the immense impact of the Coronavirus epidemic and the subsequent focus it has inherently placed on society's safety and wellbeing through maintaining social distancing as the core problem. The next step is action planning or targeting the change. 'Action' refers to what the researcher is doing and involves considering their circumstances, how and why they got there. The target focus within this paper is to observe and analyse how people interact and move within a space per social distancing regulations, observing the outcomes and synthesising the data to find potential causes. Action taking then puts the plan into action leading to the evaluation of outcomes and specifying learning. This final phase is inclusive of ongoing reflection that is undertaken throughout the research process. By evaluating each step of the project, a record of all findings and observations will be documented, potentially assisting in further development.

As this project seeks to develop a digital artifact, a design research methodology will be followed alongside action research. Design research is defined as a process consisting of activities concerned with the construction and evaluation of technology artifacts (Cole et al. 2009) in comparison to action research, which follows theoretical concepts. Design research is cyclic, implementing an iterative process. A workflow is developed to define the procedures that need to be followed to create a digital artifact.

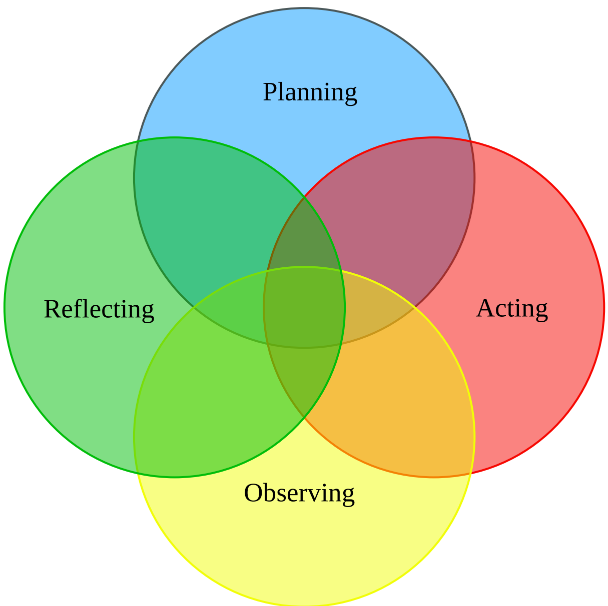

Figure 1.a. Action Research Workflow

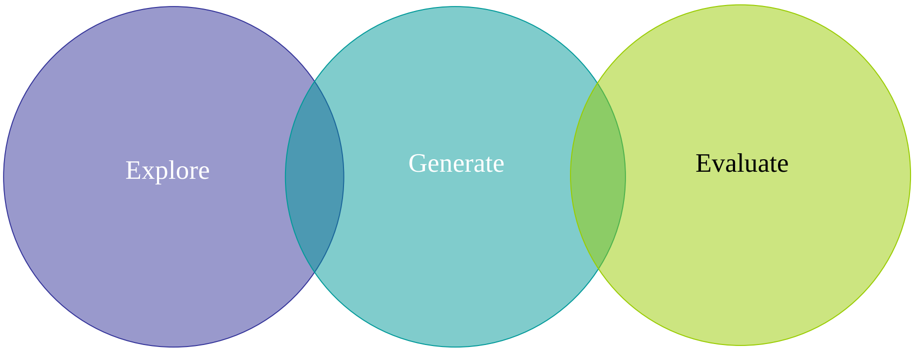

Figure 1.b. Design Research Workflow

5. Background Research/Literature review

COVID-19 AS A SPATIAL ISSUE

In today's current climate, we are faced with several societal issues that stem from the development of the epidemic that is COVID-19. COVID-19 has rapidly changed society and the way we live as well as the way we interact with and use spaces. Spatial analysis and big data technology can be used to analyse and provide responses with a supply of information about the pandemic dynamics. These analytical responses can help in understanding if rules and controls put in place to stop the spread are being followed and if they are working as intended (Zhou et al. 2020, p. 78). GIS and big data technologies have also been assisting with the visualisation of epidemic information, spatial tracking, prediction of transmission and spatial segmentation of the epidemic risk and prevention level, providing spatial information support for decision-making, measures formulation, and effectiveness assessment of prevention and control (Wang et al. 2019). In the research paper “Spatial epidemic dynamics of the COVID-19 outbreak in China”, the spatial epidemic dynamics of COVID-19 are explored, confirming that spatial association of the infection exists and helps immensely in understanding the spread of disease (Kang et al. 2020). Through the synthesisation of found data from spatial analysis in according with COVID-19, major lessons can be learned to aid in post-COVID urban planning and design (Sharifi et al 2020).

ADDRESSING NON-DIGITAL ISSUES DIGITALLY

With access to an array of complex technologies and digital methodologies, social justice issues can be addressed with the use of technology regardless of whether the topic of focus is digital or non-digital. Within Karunakaran's paper "Organisation of Pedestrian Movements: An Agent-Based Approach", focus is placed on addressing real-world physical problems through digital means even though the issue at hand is not digital. The paper explains that whilst there has been much development within urban modelling, it is still in a nascent state in comparison with digital advancement (Karunakaran 2005). By investigating and analysing pedestrian movements and looking at the phenomena of self-organisation within urban space, we can look at a non-digital space digitally, in turn helping us understand the relationship between people, place and design (Karunakaran 2005). The notion of using complex technologies to address societal issues reinforces the benefits of utilising Machine Learning to address and evaluate social distancing.

ANALYSING PEDESTRIAN PATTERNS THROUGH SPATIAL ANALYSIS AND MACHINE LEARNING

Spatial analysis seeks to explain patterns of human behaviour and its spatial expression in mathematical and geometrical terms (Mayhew 2004). Spatial analysis should be used to reinforce the social operation parameterisation of models and methods, especially when managing social issues (Zhou et al. 2020, p. 77). The benefits of pairing Machine Learning with spatial analysis to identify and evaluate pedestrian movements include flexibility, accuracy, cost, and the ability to acquire people distribution information (Vuksanovic et al. 2018). High flexibility is due to the increase in free access to Machine Learning, specifically object detection software on any device in any resolution, in turn, decreasing costs. Machine Learning has been developing and evolving since 1952 (Foote 2019), inferring that it has reached a new level of cognition that can provide high levels of accuracy. This renders it an effective tool in analysing pedestrian movement and providing distribution information (Vuksanovic 2018). Object detection is fundamental to the study of pedestrian flows, especially when referencing social distancing and has been used as a method for identifying people and their behaviours for many years. In the paper “A Trainable Pedestrian Detection System”, first published in The Proceedings of Intelligent Vehicles, Stuttgart, Germany in October 1998, Papageorgiou, Theodoros, Evgeniou, Tomaso and Poggio present a trainable object detection system that automatically learns to detect objects of a certain class in unconstrained scenes. The paper aims to detect pedestrians without relying on hand-crafted models and motion information, rather teaching the system to identify pedestrian models from examples using no motion cues (Papageorgiou 1998). Computational systems have become increasingly proficient in detecting objects that the possible applications of object detection research to practical problems are significant.

6. Case Study

This case study seeks to address the research aims through the development of an AI-based monitoring system utilising a JavaScript workflow. This tool was developed in collaboration with Pulse Software, implementing an iterative design process. The initial choice made for executing this project was RunwayML and Grasshopper; however, after testing and creating smaller prototypes, JavaScript was chosen due to prior knowledge and familiarity with the researchers. Machine Learning platforms are also easily accessible through JavaScript, inferring website development, ML object detection and distance measuring can all be developed within the one piece of code, streamlining information, and preventing overcomplication. This script can easily be shared and accessed by anyone as it has no dependencies aside from needing an internet connection.

6.1 INITIAL MACHINE LEARNING TESTING

The initial stage of developing a digital prototype consisted of testing and selecting the software. RunwayML, a platform that allows users to browse and create Machine Learning models, was tested first. RunwayML is simple to use as it did not require any installation and had several object detection models that defined people within a video frame, however, it was not possible to load live data and have an automatic instant output. Another alternative that was considered was Teachable Machine, a web-based tool that enables the creation of Machine Learning models by training a user’s computer to recognise their images, sounds and poses. This tool was very efficient at detecting people and could be trained to learn what social distancing looks like; however, it does not take actual distances into account and therefore would not be best suited to this project.

Through the recommendation of industry professionals at Pulse Software, the final choice was made to utilise TensorFlow, an open-source platform for Machine Learning that can be called upon in JavaScript to allow the script to detect people. JavaScript can then be used to create a web application, find the centre-points of people detected and measure the distance between them, allowing all elements of the project to be executed within the same script.

Figure 2. RuwayML and TensorFlow were both ML platforms considered

6.2 CAMERA SET UP

6.2.1 IP Web Camera Smartphone Application

The first phase of the project workflow is concerned with the video input. The most efficient way live video footage can be captured anywhere by anyone is through the use of smartphones; This led to the decision of using an IP Web Camera Application available for download on both Apple and Android devices. The application opens the phone's camera, providing the IP address (Figure 3.) which will later be entered in the developed web page to be analysed.

The only limitation with utilising this method is that the internet (Wi-Fi address) needs to be the same for both the device showing the webpage and the mobile device using the application.

Figure 3. IP Web Camera Application

6.2.2 IP Camera Positioning and Distance Approximation

Positioning the camera is a crucial factor within this workflow, as this is how the set 1.5 distance measurement will be found. The camera set up for this research project will be fixed in the top corner of an office space, showing a wide-angle view of the space and the people within it. From here, it was found that a 1.5-meter-long table constitutes to 200 pixels within the video frame. Two hundred pixels will now be the unit of measurement used throughout the script.

6.3 WEBSITE DEVELOPMENT

6.3.1 Displaying Video Output Using IP Address

A webpage was developed using JavaScript that allows an IP address to be entered and loaded. This webpage will be where the live video footage is viewed and later monitored and analysed (Figure 4.).

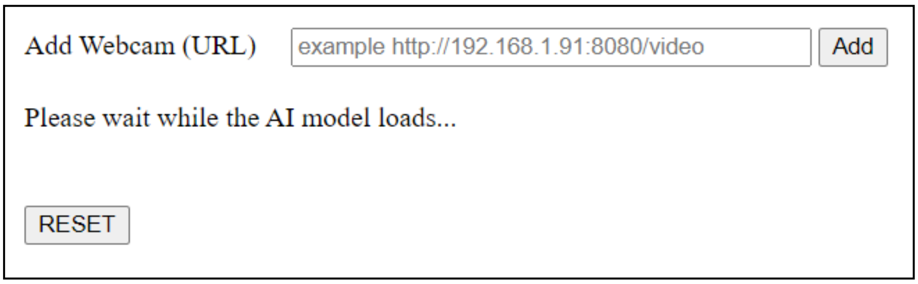

Figure 4. Basic Web Page Layout

6.3.2 Setting Up Camera View and Canvas

The camera view was created using a Camera Container (CamContainer) (Figure 5.) that has a text input allowing for an IP address to be entered. A placeholder was used to avoid re-entering the same IP address whilst in the development and testing phase. A canvas was then created on top of the container (Figure 5.); This will allow for bounding boxes and centre points to be drawn over the video in the next stage of development.

```
<div id="addCamContainer" class="section">
  Add Webcam (URL)<input id="camUrl" type="text" placeholder="example http://192.168.1.91:8080/video" value="http://192.168.1.91:8080/video"/>
  <button onclick="addCamClicked()">Add</button>
</div>
<div id="camContainer" class="section">
  <canvas id="canv" />
</div>
```

Figure 5. Camera Container and Canvas Created

6.4 MACHINE LEARNING AND PEOPLE DETECTION

This step was integral for the development and progression of the prototype as the following steps are all dependent upon recognising and identifying people within the frame. Many issues were faced during this phase as bounding boxes were not lining up correctly with people which was ultimately a result of canvas and camera container misalignment. The workflow (Figure 6.) for this final phase ultimately included taking the video input and applying object detection to filter the "People" class to ensure only people were being identified. Once people were detected, bounding boxes and centre points are drawn so the distances between centroids can be computed. Once distances have been defined, the code will examine how many pixels apart people are from each other. Results will be shown accordingly.

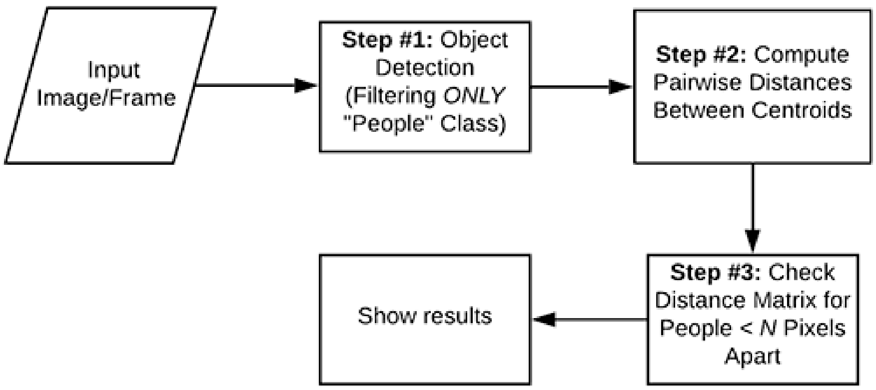

Figure 6. Machine Learning Workflow

6.4.1 Utilising TensorFlow

TensorFlow model sources were added into the script to allow the models to be called upon later in the code (Figure 7.). These models allow a live video feed to detect objects, including people.

```
<script src="https://cdn.jsdelivr.net/npm/@tensorflow/tfjs"> </script>
<script src="https://cdn.jsdelivr.net/npm/@tensorflow-models/coco-ssd"> </script>
```

Figure 7. TensorFlow Model Sources

6.4.2 Drawing Bounding Boxes Around People

People detected in the frame were called using "peeps" function. For all "peeps", a rectangle was drawn by finding the four furthest corners of the person (Figure 8.). The style will later be defined, with the style colour dependant upon the distance.

```
for (let i=0; i<peeps.length; i++) {
  console.log(peeps[i]);
  // draw bounding box around person
  ctx.beginPath();
  ctx.rect(peeps[i].bbox[0] * xMultiplier, peeps[i].bbox[1] * yMultiplier, peeps[i].bbox[2] * xMultiplier, peeps[i].bbox[3] * yMultiplier);
```

Figure 8. Drawing Bounding Boxes around People

6.4.3 Finding the Centre Points

To find the centre points of people, the bounding box was measured half-way down the x and y axes to find the middle (Figure 9.).

```
// draw center point
let x = (peeps[i].bbox[0]) + ((peeps[i].bbox[2]) / 2);
let y = (peeps[i].bbox[1]) + ((peeps[i].bbox[3]) / 2);

peeps[i].x = x;
peeps[i].y = y;
```

Figure 9. Drawing the Centre Points

6.5 DISTANCE DETECTION

6.5.1 Euclidean Distance Formula

When measuring the distance between people, the Euclidean Distance Formula is used. According to the Euclidean distance formula, the distance between two points with coordinates (x, y) and (a, b) is given by $dist((x, y), (a, b)) = \sqrt{(x - a)^2 + (y - b)^2}$ (A. Bogomolny 2018). The distance set as 1.5 meters is 200 pixels and is used here to find if people are staying 200 pixels apart. This loop will continue to run to find the distance between all people in the frame (Figure 10.).

```
function calcDistance(peep1, peep2) {
  let distPixels = Math.hypot(peep2.x-peep1.x, peep2.y-peep1.y);
  if (distPixels < 200) {
    console.log("*********************************");
    return true;
  } else {
    return false;
  }
}
```

Figure 10. Finding the distance between people

6.6 VISUALISING AND UNDERSTANDING THE DATA

Now the script takes in the video input, displays it on a web page, detects people and finds the distances between them, the data needs to be visualised in a simple way that can be identified quickly and efficiently. Using the bounding box and centre point styles, the colour is set depending on the distance of people from one another. When people are 1.5 meters apart or further, their bounding boxes are green. When they are closer than the required distance, they change to red. Within JavaScript, a function "isClose" was created to define when people are closer than 1.5 meters. When this function is true, and people are closer than 1.5 meters, the stroke style of the bounding box is set to red. When this statement is false, and people are further than 1.5 meters apart, the stroke style is set to green (Figure 11.a.).

Due to COVID-19 restrictions and working from home arrangements, initial testing was conducted using static images of people. By pointing the IP web camera at the images, the tool was able to detect the distance of the people from one another. This testing method was not always wholly accurate as the angle and position of the camera were different for each image used; however, it was working as expected (Figure 11.b.).

```
ctx.beginPath();
ctx.rect((x-2) * xMultiplier, (y-2) * yMultiplier, 2, 2);
if (peeps[i].isClose) {
  ctx.strokeStyle = "#FF0000";
} else {
  ctx.strokeStyle = "#00FF00";
}
```

Figure 11.a. isClose Function renders bounding box green when false (people are > 200 pixels) and red when true (people are < 200 pixels)

Figure 11.b. Visualising Social Distancing: Left image showing two people < 1.5 meters, right image > 1.5 meters

6.7 TESTING AND DEBUGGING

During the testing phase, the camera was set up in the top corner of an office space and pedestrians within the room were detected and monitored (Figure 12.). This process consisted of iterative testing and debugging when issues were faced until the most effective model was reached. To determine maximum effectiveness, the tool needs to:

A. Detect all people within the frame regardless of their position within the space or distance from the camera.
B. Draw a bounding box with centre point that correctly surrounds each person, with the centre point meeting the centre of the person regardless of whether they are seated or standing, stationary or in motion.
C. Show a green bounding box and centre point for all people who are social distanced (> 1.5 metres apart); and,
D. A red bounding box and centre point for all people who are not adhering to social distancing regulations (< 1.5 metres apart).
E. Show a real-time analysis of what the website is detecting in the console.

Figure 12.a. Two socially distanced people shown in webpage and console view

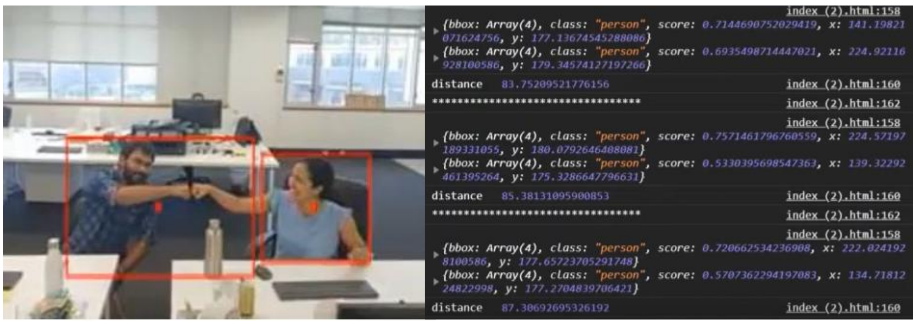

Figure 12.b. Two people not socially distancing shown in webpage and console view

7. Discussion (evaluation and significance)

Through a cyclical research process and iterative design, this research has successfully demonstrated that through the utilisation of Machine Learning, an AI-based monitoring system employing real-time data can be developed and used to identify and evaluate social distancing. Through ongoing evaluation, there are factors that this paper and digital artifact were not able to address due to a restricted timeframe. Whilst the developed tool aligns with the aim of the paper it should be noted that for the most accurate results, future development should include camera calibration through intrinsic and extrinsic parameters to allow pixels to be mapped to measurable units. Whilst delivering an approximated analysis of pedestrian movements following COVID guidelines, currently, pixel distances are strictly relied on, resulting in less accurate findings and data. For an even more accurate evaluation, a top-down transformation of the viewing angle could be implemented, allowing for the application of distance calculations to the birds-eye view of the specified space, leading to a better approximation of pedestrian distances. With further research resulting in an expanded skillset, achieving a model that is mapped in measurable units, this tool has the capacity to achieve more accurate results. Whilst this paper successfully developed a detection tool that aligns with the initial aims and objectives, it should be viewed as the foundations or starting point for further developments.

This tool can be developed on a larger scale, with cameras potentially being set up on drones to monitor and analyse beaches, parklands, or railways. This tool could not only tap into stopping the spread of disease but evaluate how spaces are used if they are being used effectively and efficiently and how they could be reimagined or redesigned to accommodate people better. Further factors that could be considered include privacy protection of pedestrians, depth sensing and providing a pedestrian count.

Regardless of the current limitations, the development of this tool has positive implications for the future of COVID-19 social distancing regulation and analysis and programming and analysing computationally. Through the utilisation of JavaScript and Machine Learning in a spatial context, computational, architectural, and urban industries are merged, creating a crossover that could provide an answer to combating this physical, real-world problem digitally.

8. Conclusion

Through research and design, Machine Learning can be implemented to detect social distancing using real-time data. Revisiting the initial research question: "How can Machine Learning be utilised to spatially analyse real-time data to detect social distancing in public spaces?" It has been proven that through the use of Machine Learning employed through JavaScript, pedestrian patterns can be detected in a space. This study has explored the viability of utilising object detection tools to analyse real-time data, proving that it is possible through the employment of computational and mobile digital technologies. As this research was only conducted over a ten-week period, there is the potential for further development and advancement. Previously mentioned limitations and setbacks seek to provoke further thought into the investigation of depth sensing and pixel mapping through camera calibration, leading to a more accurate detection system. Through the utilisation of Machine learning and spatial analysis, we can evaluate the correlation between movement patterns in public spaces and social distancing regulations. As COVID-19 restrictions are no longer in a nascent state, practising social distancing has become the new norm; To design and plan for the future, we must identify and evaluate pedestrian patterns through monitoring social distancing.

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