# Big Data Helps for Non-Pharmacological Disease Control Measures of COVID-19

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## INTRODUCTION

During the COVID-19 pandemic, a variety of non-pharmacological disease control measures, including travel restrictions, lockdowns, stay-at-home orders, wearing-a-mask policies, and social distancing regulations, have been implemented by governments and lawmakers. Issuing travel restrictions or lockdown policies can help to mitigate the spread of COVID-19 by reducing human mobility and decreasing the probability of contact (Grépin et al., 2021). It is more important to keep social distancing now claims than ever before, since it is one of the best ways to prevent the spread of the disease except wearing face masks (Milne & Xie, 2020). Wearing masks can significantly reduce the amount of coronavirus transmitted by droplets and aerosols (Eikenberry et al., 2020). Almost all countries now carry out such non-pharmacological disease control policies as mandatory strategies. Based on the proposed requirements by the WHO, the minimum distance between individuals must be kept at least 6 feet to achieve a safe social distancing among the people. The medical researchers have pointed out that individuals with mild or no symptoms may also be carriers of the novel coronavirus (Wang et al., 2020), therefore it is important to require all people to maintain controlled behaviors and to keep social distancing. However, it may be a challenging task to monitor the amount of infection spread and the efficiency of the constraints.

Since the end of 2019, the lives of people all around the world have been drastically affected by the COVID-19 pandemic. The world economy has been in a depression due to a loss of jobs, while face-to-face communication has been restricted to control the infection rate (Feyisa, 2020). Although it has been more than 18 months since the global outbreak, medical researchers are still unable to confirm the end of the pandemic. Despite the effectiveness of the new vaccines by some degrees, the Delta variant leads the significant uncertainty, which makes the situation moving towards the undesired detection. Due to such the circumstance, research communities have pointed out that society may go through a long period of abnormality. Governments have to continue to enforce mask-wearing, social distancing, and quarantines. Many changes for society, including online education, mandatory facial masks, and the vast majority of people working from home, have been made in the new normal, and perhaps continue for a long time (Odusanya et al., 2020).

Cutting-edge technologies, such as machine learning, deep learning, computer vision, and big data analytics, can be applied to implement efficient non-pharmacological disease control measures (Lakhani

DOI: 10.4018/978-1-7998-9220-5.ch009

et al., 2020). Motivated by the current demand in disease control for Covid-19, this chapter is designed to investigate how such technologies work to solve a broad range of real-world problems, such as tracking and visualizing stay-at-home measurements, monitoring social distancing regulations, and detecting face-mask-wearing practices. The objectives of this chapter are listed as follows:

- illustrating how big data helps in measuring human mobility to track stay-at-home measures with information retrieval and visual mining.
- investigating how deep learning and computer vision work for implementing a social distancing monitor using a pre-trained detector, i.e. YOLO v3.
- examining how to detect whether individuals wear masks or not using deep learning approaches, along with a real-world testing process.

## BACKGROUND

COVID-19 is a highly infectious and crafty virus. In most cases, the infected individuals do not initially exhibit symptoms, while some remain asymptomatic. Thus, a non-negligible fraction of the population can, at any certain time, be a hidden factor of transmissions. In response, governments in many countries have took much effort to develop contact tracing apps for smartphone that help solve the difficult task of tracing all recent contacts of newly confirmed infected individuals (Ahmed et al., 2020). Additionally, it is still challenging to understand the actual human mobility responding to the stay-at-home policies due to the lack of a recorded and large-scale dataset that can describe human mobility during the pandemic (Xiong et al., 2020). Based on the development of big data technologies over the last decade, government departments widely adopt location data of mobile device to analyze human mobility, in order to support policy-making objectives. Researchers also use location data in aggregate shape to further understand general patterns of human movements and behaviors according to the global positioning system (GPS) signals, cell site locations, and bluetooth beacons (Bachir et al., 2019; Song et al., 2010; Stange et al., 2011). Through such analysis, governments and researchers can navigate the spreading of the COVID-19 outbreak and the effectiveness of public health interventions can be measured. COVID-19 mobility tracking programs have been proposed on several platforms which can evaluate human travel distance. Those platforms covers Google's community mobility reports, Apple's mobility trends reports, and Cuebiq's COVID-19 mobility insights. Researchers have applied data extracted from Facebook for Good program to establish the model of mobility patterns in Seattle, in order to quantify its effect on the COVID-19 outbreak (Burstein et al., 2020). However, such studies and reports are restricted to the aggregated level of travel distance due to the lack of individual-level measurements.

With the revolutionary development of the computer hardware capability, based on learning algorithms, the more accurate models and faster monitors can be generated by researchers and scientists, compared to regular machine learning models. Deep learning models, such as convolutional neural networks (CNNs) and deep neural networks (DNNs), have been applied in feature extraction and complex object classification (Gidaris & Komodakis, 2015). These models can also be performed to achieve social distancing monitoring. Punn et al. (2020) developed a DNNs-based monitor for detection of human mobility, which can measure the number of individuals who violated the social distancing. Based on various research objectives, similar studies have been conducted by researchers, which includes detecting the people distancing in a certain manufactory (Khandelwal et al., 2020), monitoring social distancing constrains in crowded scenarios (Sathyamoorthy et al., 2020), and assessing infection risk