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Editorial

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It Is Time to Modernize Disaster Preparedness With Crowd Analysis

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In this issue of the *Journal of Acute Medicine*, Fiandeiro et al. present a review article entitled "Modernized crowd counting strategies for mass gatherings—a review.[1]" Early last year, we all witnessed an unprecedented and horrific human stampede event during Halloween festivities in Seoul, Korea. Along with many other events, such as a recent fatal crush during the first night of the Astroworld Festival held at NRG Park in Houston, Texas led to 10 deaths and over 300 injuries in 2021, we believe it is time to modernize methods for disaster preparedness with crowd analysis. As some important historical insights provided by Hsieh et al.[2] and Ngai et al.[3], events that occurred in developing countries and outdoors were associated with increased fatalities. However, before we apply and invest in the technology to monitor the critical crowd statistics and crowd behavior, readers in our journal should be familiar with crowd taxonomies, potential of modern deep learning methods, and strategies to deal with potential disaster incidence.

As Bendali-Braham et al.[4] proposed in their review article, most researchers categorize crowd analysis into crowd statistics and crowded scene analysis (Fig. 1). While event planners might care the most about crowd statistics, emergency service responders would pay more attention to crowd behavior, motion tracking, and prediction. With the help of deep learning methods, anticipating crowd movement patterns and real-time crowd density estimation to avoid potential catastrophes would be possible. Nowadays, commercial companies are attempting to provide service to the related stakeholder, and open-source Python codes are also available on public platforms.[3,5] Accordingly, we urge the related government agency, event planners, public health practitioners, and emergency service responders to validate and implement such state-of-the-art technology to prepare for potential catastrophic disasters.

For those who still need clarification regarding the mechanism of machine learning and deep learning on crowd analysis, except for the review article that we published in this issue, Bendali-Braham et al.[4] provided in-depth technical review of both historical and state-of-the-art crowd analysis methods. In brief, the multi-layered convolutional neural network (CNN)[6], Edge Boxes algorithm[7], and DeepParts[8] are promising for region proposals on pedestrian detection. For group detection, top-down approaches start from a crowded scene,[9-11] and then segment into small groups and bottom-up approaches start by detecting pedestrians and then create clusters of them[12-14] are available and promising.

In addition, multi-task CNN, crowd behavior recognition, and anomaly detection are of particular research interest that our readers might be excited to validate for disaster preparedness. With these methods, we would be able to implement higher-level cameras from the drone to include the larger scale of the crowd image, lower-level surveillance cameras to include the higher resolution crowd image, and some other non-image data such as the sound in the environment, message delivery to the police or the emergency medical service. However, how to define and annotate anomaly in crowd behavior still need consensus and further evaluation.

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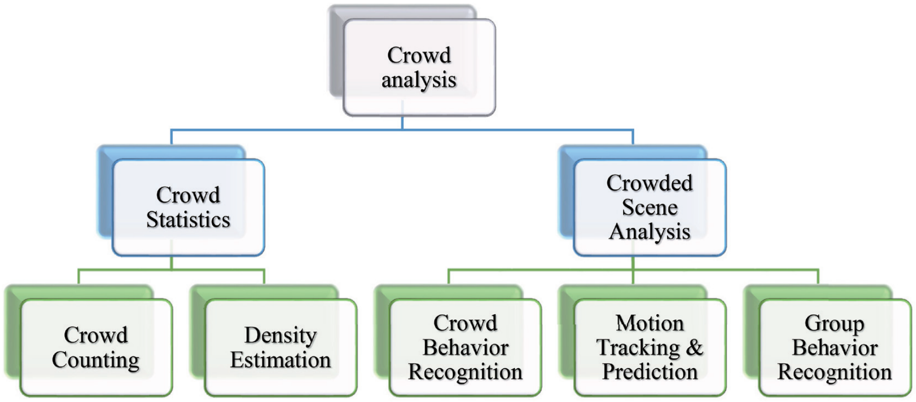

Fig. 1. Taxonomies of crowd analysis.

As Fiandeiro et al.[1] presented in this issue of our *Journal of Acute Medicine*, the same model could have very different performances in different datasets. For example, the same context-aware model proposed by Liu et al.[15] could have very different mean absolute errors in different datasets, ranging from 7.8 to 212.2. We believe it could be attributed to the different sizes of the crowd in these different datasets (the UCF CC50, Shanghai A, and Shanghai B datasets), and we urge the researchers to systematically compare the models with consistent metrics, as well as the pooled overall estimated accuracy with confidence intervals.

Furthermore, different reviewers all pointed out the same obstacle that prevents us from applying the method in the fields: the need for more diverse datasets to test their theoretically better models. As an old anecdotal quotation, we often prepare for previous but not future disasters. In other words, testing new methods on the old datasets would be filling new wines in the old wineskins, and "the wine will burst the skins." Many other needs exist to compare the same model, such as different light sources, colors of clothes, and different resolutions of the image. From the perspective of a data scientist, it is now time to systemically design data acquisition, method validation, and effectiveness evaluation for crowd analysis.

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