International Journal on Advanced Science Engineering Information Technology

Vol.14 (2024) No. 1
ISSN: 2088-5334

Development of a Risk Space Prediction Model Based on CCTV Images Using Deep Learning: Crowd Collapse

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***Abstract*—Crowd disasters are not limited to events but can occur at any time and place where large crowds are densely gathered. The most significant factor contributing to injuries in mass gatherings is pressure. The likelihood of injuries due to pressure significantly increases when the crowd density exceeds 5-6 individuals per square meter. Once a crowd disaster occurs, it becomes challenging for rescue and medical personnel to access the affected area, potentially exacerbating the situation. However, since there is no single clear solution to address crowd disasters, there is a need for a system that can detect and analyze them in advance or in real-time. This research aims to contribute to the proactive detection and analysis of various crowd disasters, focusing on improving strategies for disaster response. In this study, we utilized a dataset of 50 videos from 35 individual incidents to propose a framework that classifies the risk levels into Crowd Crush, Crowd Wave, and Crowd Collapse. Additionally, we analyzed the feasibility of real-time detection using P2PNet (Point to Point Network), Yolo (You Only Look Once) v8, and DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithms, moving away from prior still image-based detection methods. Our research outcomes provide new evidence for the feasibility of real-time detection using DBSCAN in Crowd Disaster scenarios. Moreover, the findings from this study can serve as valuable reference material for upcoming research, particularly emphasizing the algorithmic analysis of crowd collapses.**

***Keywords*— Crowd disaster; crowd crushes; crowd collapses; P2PNet; YOLO; DBSCAN**

Manuscript received 11 Nov. 2023; revised 20 Dec. 2023; accepted 12 Jan. 2024. Date of publication 29 Feb. 2024.

I. INTRODUCTION

The primary cause of fatalities in various international mass gatherings is injuries resulting from pressure. This occurs due to crowd crush, crowd waves, and crowd collapses [1]. Crowd disasters are not limited to events but can happen at any time and place where large crowds are densely gathered [2]. This inherent risk underscores the importance of comprehensive safety measures and emergency preparedness in locations with significant crowd density. The probability of accidents increases substantially when the crowd density surpasses the critical threshold of 5-6 individuals per square meter [3]. Crowd disasters persistently occur worldwide, indiscriminate in advanced or developing nations, constituting a disaster with significant ramifications and impacts on society [4].

On Saturday, October 29, 2022, around 10:00 PM, a significant stampede incident occurred in a narrow alley on the west side of Hamilton Hotel in Itaewon-dong, Yongsan-gu, Seoul, South Korea, as a large crowd gathered to enjoy a Halloween festival. At the time of the accident, a bottleneck occurred in a space measuring approximately 18.24 square meters, exceeding the capacity of the space by more than seven times (density of $12/\mathrm{m}^2$). This phenomenon led to people being pushed and jostled, resulting in what is commonly referred to as a "chain trampling." Ultimately, this incident resulted in 159 fatalities and 196 injuries [5].

The incidents themselves have little time to deal with, making them susceptible to casualties, especially when victims experience compromised consciousness due to suffocation. Moreover, within densely populated and chaotic environments, the accessibility and transportation of injured individuals pose significant challenges for medical personnel [6]. Despite these challenges, a clear and definitive solution for such incidents has yet to be identified. In the aftermath of the incident, as response and rescue become challenging, there is a need for a system and framework that can analyze and assess the risks associated with crowd density in real time.

Therefore, this study aims to propose a framework for classifying risk levels and detecting crowd collapse incidents using deep learning. Furthermore, in this study, we perform crowd disaster detection using CCTV images by applying P2PNet, Yolo.v8 and DBSCAN algorithms, away from existing still image-based detection method [7]. Through this, we aim to prevent crowd disasters by developing technology that can pre-detect stages such as crush, wave, and collapse in real-time images and situations.

A. Crowd Disaster

In crowd disaster, force chains can form within densely packed crowds due to unintentional physical interactions among individuals. These chains can result in significant fluctuations in crowd pressure [8] [9], ultimately leading to a crowd collapse. Typically, crowd disasters involve three interconnected elements: overcrowding causing a crowd crush, waves or movements in a densely packed crowd, and crowd collapse. Figure 1 illustrates the process of crowd collapse.

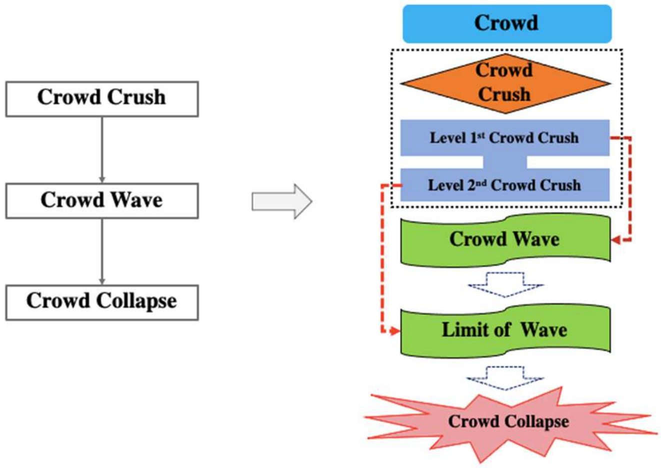

Fig. 1 Progression of crowd collapse

1) Crowd Crush: If an excessive number of people gather in a restricted area and this situation persists, the population density within the crowd becomes too high. Consequently, individuals may lose control of their body movement, resulting in what is known as a crowd crush [10]. Crowd crush can be broadly divided into two stages. The first stage occurs when the cluster density reaches 8 individuals/m² due to the sustained influx of subsequent clusters following cluster residency, initiating the cluster wave phenomenon. In the second stage, within high-density cluster residency conditions, the continuous influx of subsequent clusters leads to a cluster density exceeding ten individuals/m², resulting in overcrowding and initiating limit of the wave.

2) Crowd Wave: As the average density of the crowd increases, there is a sudden transition to unstable flows. These irregular flows were marked by spontaneous and unpredictable movements in all possible directions, causing people to be pushed around [11]. Due to the disparity in the distribution of cluster density and pressure, unintended vibrations occur. Subsequently, a notable shaking phenomenon, the 'limit wave,' emerges, often accompanied by cluster waves and crisis avoidance behavior. This may escalate into a serious incident, such as a crowd collapse.

3) Crowd Collapse: Crowd collapse is the breakdown of mutual support among individuals. The repetitive pattern of oscillation between movement and halting leads to a weakening of support for individuals, and simultaneously, the pressure from people at a distance becomes concentrated in vacant spaces. The dispersion of this pressure creates larger voids, resulting in people falling and forming a hole. The pressure exerted on individuals around this hole pulls in more people, thus producing a pile of wedged bodies [12].

B. Detection of Crowd Disaster Situations and Spatial Elements Using P2PNet, YOLO, and DBSCAN Algorithms

Understanding and predicting high-risk areas becomes crucial given the increasing challenges in managing crowd disasters. Previous research has demonstrated the effectiveness of data mining algorithms such as P2PNet, YOLO, and DBSCAN in object detection. This study aims to develop a predictive model for high-risk areas in crowd-disaster situations by combining these algorithms with deep learning techniques. Therefore, integrating these advanced technologies can enhance our ability to anticipate and respond to crowd disasters more effectively. Table 1 provides an overview of previous research on detecting crowd disaster situations and spatial elements.

TABLE I
PREVIOUS RESEARCH ON THE DETECTION OF CROWD DISASTER SITUATIONS AND SPATIAL ELEMENTS

Researcher	Method	Results
Q. Song et al. [13]	P2PNet	Propose "Density Normalized Average Precision"
L Yajing [14]	YOLO	Detect abnormal behavior in crowd scenarios
Eiman Kanjo [15]	DBSCAN	Propose overcrowding detection system, “Crowd Tracing.”
P.S. Karthika et al. [16]	Space syntax	Distance detection and walk accessibility during crowd disasters.
W shu et al. [17]	Frequency Domain	Establish the groundwork for a new crowd-counting model.
Tarik Reza Toha et al. [18]	LC-Net	Count individuals in dense crowds through crowd localization mapping.
H Xu et al. [19]	YOLO	Verification of YOLO-CS Performance in Crowd Videos.

1) P2PNet: P2PNet is a notable algorithm for assessing crowd density, delineating multiple-crush spaces, and acting as a criterion for detecting spatial elements based on the coordinates of that space [20]. P2PNet partitions the acquired feature map into a grid using a stride length of s. In this grid, each cell is designated as a potential head candidate or proposal, and it is assigned a confidence score. This strategy is commonly known as a "one-to-one match" [21]. Additionally, P2PNet utilizes a series of convolution and pooling layers to extract features from input images, capturing key points that correspond to characteristics of a crowd. These key points serve as the foundation for structuring the data.

2) YOLO: Recognizing all individuals in the image poses a challenge for computational systems due to the size difference caused by their varying distances from the camera. The issue of vertical size change is prevalent in nearly all datasets, necessitating consideration in the majority of crowd-counting methods. Employing detection methods with diverse sizes of detection boxes, such as YOLO, effectively addresses this challenge [22], [23]. YOLO is characterized by dividing an image into a grid and simultaneously predicting bounding boxes for objects and their class probabilities within each grid cell. This allows YOLO to exhibit excellent performance in real-time object detection [24], [25].

3) DBSCAN: Non-hierarchical clustering analysis is suitable for extensive data analysis, as it avoids measuring distances between all data points. DBSCAN (Density-Based Spatial Clustering of Applications with Noise) removes the necessity of specifying the number of clusters in advance. Within a defined radius "R," if there are "n" or more data points, they form a single cluster, and data points not belonging to any cluster are classified as Noise [26]. This occurs when clustering conditions are not met, defined by ε (epsilon) as the radius around a specific point and the requirement for a minimum number of points (Min Point) inside the cluster. Consequently, Noise not belonging to any cluster can be designated as the cluster boundary point [27].

II. Materials and Method

This study aims to construct a database for analyzing and evaluating risks associated with crowd disasters, developing measurable indicators, and proposing the predictability of risk situations by applying algorithms. Figure 2 below illustrates the main processes of this study.

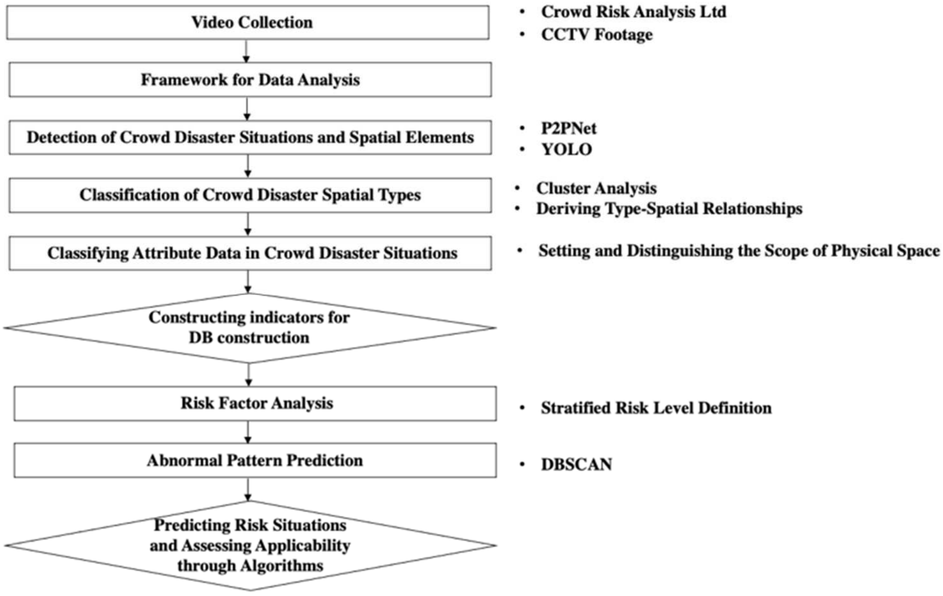

Fig. 2 Research Main Processes

This study made a substantial effort in the video collection process, where 50 video datasets pertaining to 35 distinct crowd disaster incidents were meticulously gathered. This collection includes videos listed on the Crowd Risk Analysis Ltd website, accounting for 25 datasets, and an additional ten datasets representing more recent crowd disasters not listed on the website. This comprehensive collection ensures a wide range of incidents are covered, providing a diverse and relevant dataset for analysis. Table 2 in the study document details the list of included crowd disaster incidents, offering a clear and organized overview of the data sources utilized. This table not only enumerates the incidents but also serves as a reference point for understanding the variety and scope of the crowd disasters analyzed, which is crucial for the depth and validity of the study's findings.

TABLE II
CROWD DISASTER INCIDENT LIST

Year	Event	Year	Event
1989	Hillsborough	2015	Rath Yatra
1993	Camp Randall	2015	Hajj
2005	Oasis Concert	2016	Thanksgiving
2006	Lotte World	2017	UEFA Champions League
2009	Millennium point	2017	Demba Diop
2010	Kumbh Mela	2017	Stade de la Licorne
2010	Makhulong	2018	Sterophonics Concert
2010	Electric Daisy	2019	Patum de Berga
2010	Love Parade	2019	Bumbershoot Festival
2012	Johannesburg Univ.	2019	Parramata Shopping Centre
2012	Madrid Arena	2021	Meron
2013	Kumbh Mela	2021	Astroworld Festival
2013	San Fermín	2021	Vaishno Devi
2013	Xierqi subway	2022	Congress Marathon
2014	Syedna's funeral	2022	Notting Hill Carnival
2014	Nigeria Job Fair	2022	Seoul Halloween
2015	La Patum	2023	Gulf Cup final
2015	Holy River		

A. Framework

In the design of this study's framework, a primary challenge lies in the systematic classification of information to enable effective analysis of crowd disaster metrics. This process is instrumental in developing risk space indicators and constructing a comprehensive database. The framework includes eleven categories. 'Type of Disaster' provides a fundamental classification of incidents. The 'Date' and 'Day of the Week' categories are crucial for organizing data and identifying potential patterns or specific conditions related to the incidents, such as whether certain days are more prone to disasters. The 'Season' and 'Quarter' categories offer insights into how a time of year affects disaster likelihood, with 'Season' focusing on the impact of weather conditions and 'Quarter' showing the distribution of incidents throughout the year.

The 'Climate' category also considers the local environmental conditions that could influence crowd behavior and the likelihood of incidents. The 'Time' of the event is crucial for understanding the disaster's dynamics and coordinating swift response efforts. 'Location' and 'Venue', along with the more detailed 'Venue Specific' information, provide a nuanced understanding of each incident's geographical and physical context, which is essential for risk assessment and emergency planning. The 'Event' and 'Gathering Purpose' categories delve into the nature of the gathering, distinguishing between spontaneous events like protests and riots and scheduled events like religious pilgrimages and sporting events, which are critical for understanding crowd dynamics and implementing effective prevention and response strategies.

This extended framework thus not only categorizes crucial aspects of crowd disasters but also interconnects these elements, offering a holistic view of each event. This comprehensive approach is vital for accurate risk assessment, effective crowd management, and reducing the incidence and severity of crowd-related disasters [28]. These elements are the basic information about crowd disaster incidents. Table 3 shows the Incident Data Framework.

TABLE III
INCIDENT DATA FRAMEWORK

Classification	Content
1. Type of Disaster	① Crowd Crush ② Crowd Wave ③ Crowd Collapse
2. Date	Month-Day-Year
3. Day of Week	① Monday ② Tuesday ③ Wednesday ④ Thursday ⑤ Friday ⑥ Saturday ⑦ Sunday
4. Season	① Spring ② Summer ③ Fall ④ Winter
5. Quarter	① Q1 ② Q2 ③ Q3 ④ Q4
6. Climate	① Sunny ② Rainy ③ Foggy ④ Snowy ⑤ Sudden Showers ⑥ Typhoon or Heavy Rain ⑦ Heatwave ⑧ Lightning or Thunderstorms
7. Time	Hour: Minute: Second
8. Location	City, State, Country
9. Venue	Designation of Venue
9-1. Venue Specific	① Indoor ② Outdoor
10. Event	Designation of Event
11. Gathering Purpose	① Festival ② Carnival ③ Sports Game ④ Religious Gathering ⑤ Party ⑥ Rally ⑦ Etc ( )

In the context of a mass gathering situation, the ‘density’ of individuals or objects is a critical aspect that aids in understanding crowded scenarios [29]. the crowded level of density is divided into seven stages. With three people per square meter, the crowd has plenty of space. However, when the density goes beyond five people, the space becomes cramped, and with ten people, there's almost no room to move. As the crowd gets denser, there's physical pressure that could even cause damage to metal fences or brick walls. On average, when an adult leans to move in a certain direction, it creates a force of 260N. If 4-5 adults apply force horizontally, a person within that square meter might experience suffocation.

In a mass gathering situation, various types of objects may be present. The 'Object' category helps better understand the situation by identifying the person and characteristics of objects or those that exist. The presence of structures, the movement of vehicles along the same path as the crowd, and the proper functioning of equipment such as barriers are crucial aspects. Failure in the proper operation of such elements can pose risks to pedestrians. Therefore, the task of confirming the objects in the space is essential to detect and prevent such hazards [30]. This section allows for multiple choice. The 'Movement Direction' category facilitates understanding and predicting the dynamic aspects of crowded situations by providing information on the direction of moving subjects. Individuals within a mass gathering engage in interactions and aim to align their speeds with other crowds.

Frequently, unfamiliar individuals communicate using hand signals or adjust their walking pace or body orientation to prevent collisions with other pedestrians [31] [32]. The 'Verification Value' category provides additional information about the selected attributes. For instance, it can display the precise number of people per square meter, describe the count of objects per entity, or specify the movement direction of clusters. Table 4 below is the mass gathering situation framework.

TABLE IV
MASS GATHERING SITUATION FRAMEWORK

Classification	Attribute		Verification Value
1. Density (m^2) /Person)	① L1 (1~2person) ③ L3 (5) ⑤ L5 (7~8) ⑦ L7 (Above 12)	② L2 (3~4) ④ L4 (6) ⑥ L6 (9~11)	
2. Object	① Male ③ Child ⑤ Car	② Female ④ Structure ⑥ Animal	
3. Movement Direction	Object Coordinate Transformation		

To categorize various types of mass gathering situations and derive their relationships with physical space elements, an analysis of the physical space characteristics framework in Table 5 was conducted. The venue may exhibit a complex shape and can be divided into distinct zones based on functionality, spatial considerations, and other characteristics. Within the framework, the 'Spatial Configuration' category provides information on how the spatial layout influences crowd movement patterns and behavior. Columns and barriers that impede the natural flow of the crowd can influence the direction of crowd movement and lead to collision [33]. The 'Area' aspect signifies the size of the space, offering a scale of the area where crowds gather. Evaluating space size aids in understanding crowd size and density, informing safety and management measures. Additionally, the 'Slope' of the terrain is considered, as it can impact crowd mobility and safety. Steep slopes, for instance, may impede crowd movement, necessitating a thorough assessment of safety concerns associated with the incline.

TABLE V
PHYSICAL SPACE CHARACTERISTICS FRAMEWORK

Classification	Attribute	Verification Value
1. Spatial Configuration	① Road ② Alley ③ Square ④ Bridge	
2. Area (m^2)	S x S	
3. Slope (%)	□ %	

In the context of understanding and evaluating mass gathering situations, the 'Extent of Damage' framework plays a pivotal role, as illustrated in Table 6. This framework is crucial for a thorough assessment of the impact of crowd disasters. It includes selected subcategories like 'Deaths' and 'Injuries,' which are fundamental in providing a quantitative measure of the severity of the damage. By counting the number of fatalities and injuries, this framework allows for a precise and objective evaluation of each incident's impact.

Furthermore, this quantification is not just a statistical measure; it provides vital insights into the human cost of these disasters, reflecting the urgent need for effective crowd management and emergency response strategies. This information, detailed in the 'Extent of Damage' framework, is also instrumental in shaping policy decisions and regulatory measures to prevent such disasters in the future. It serves as a crucial data point for emergency services, event organizers, and public safety officials in planning and preparing for mass gatherings. Additionally, this framework can be used to benchmark the effectiveness of safety measures and protocols implemented in various events, providing a way to gauge improvements over time. In essence, the 'Extent of Damage' framework not only offers a snapshot of the immediate aftermath of crowd disasters but also aids in long-term planning and prevention strategies, ultimately aiming to safeguard public safety in mass gathering situations.

TABLE VI
EXTENT OF DAMAGE FRAMEWORK

Classification	Total
1. Deaths	
2. Injuries	

III. Results and Discussion

A. Experiment Data

In 2021 Meron Crowd Data: It consists of keys representing different frames. Each frame contains information about the detected persons, including their count and location coordinates. The dataset is organized into various keys, each representing a different frame (such as 'Frame_1', 'Frame_2', and so forth). Within each frame, there is detailed information about people detected by some form of an automated system. This information includes the total count of persons in the frame and their location coordinates, typically given as X and Y values on a plane. Additionally, there's a 'Metadata' section. This part of the dataset provides important details about the data collection and processing methods. It includes information about the detection method used (specified as 'P2PNet'), the types of objects that were intended to be detected (in this case, 'person'), and various image properties such as rescaling percentage, image width, and height. It also mentions the total number of frames analyzed and the frames per second (FPS) rate of the video from which these frames were extracted.

In 2022 Seoul Halloween Data: t has a similar structure to the first file, with keys for different frames and a 'Metadata' section. Each frame also details the detected persons, their count, and location coordinates. This dataset shares a structural resemblance with the 2021 Meron data. It is divided into keys representing different video frames. Like the first dataset, each frame entry in this dataset includes data on the detected persons. This encompasses both the number of persons detected in that frame and their spatial coordinates. The 'Metadata' section of this dataset also provides similar types of information: details about the detection method, the specific objects identified (again, 'person'), and various image-related metrics. This metadata is crucial for understanding the context of the data, the limitations of the detection method used, and the specifics of the image processing techniques applied.

Both datasets are evidently structured to facilitate the analysis of crowd dynamics, with a clear focus on detecting and spatially locating individuals within a series of frames. This structured approach is particularly useful for applications such as crowd movement analysis, behavior pattern recognition, and safety monitoring in crowded events.

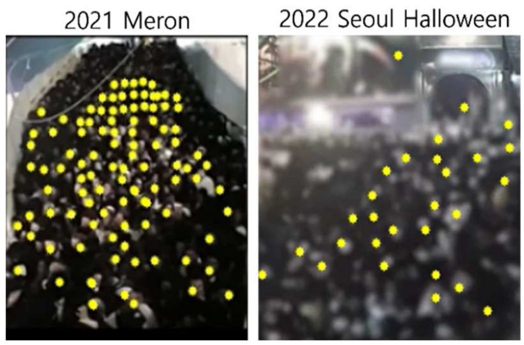

Fig. 3 Experiment Event Images

B. Experiment Result

We need to extract the location coordinates of detected persons from each frame to perform an analysis using

DBSCAN (Density-Based Spatial Clustering of Applications with Noise). DBSCAN is a clustering algorithm suited for spatial data and can identify clusters of varying shapes and sizes. It is proceeded by extracting the coordinates from the frames and then applying the DBSCAN algorithm to each set of coordinates. The analysis will reveal how people are grouped or dispersed in each frame, which could help understand crowd dynamics in these scenarios. The coordinates are extracted, and DBSCAN is applied to a representative sample of frames to understand the crowd patterns.

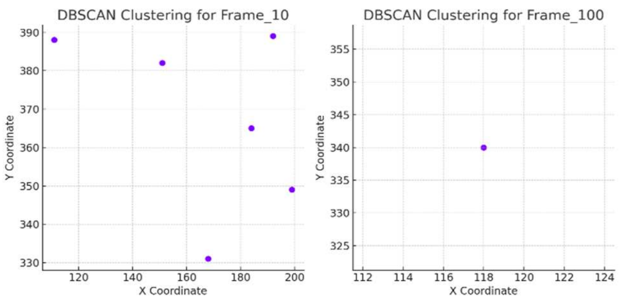

Fig. 4 DBSCAN Clustering

The DBSCAN clustering results for selected frames from the first dataset are displayed above. Each color represents a different cluster identified by DBSCAN, with noise points (outliers) typically shown in a distinct color (often purple or black). Figure 4 following, Frame 10: Shows several distinct clusters, indicating groups of people standing close to each other. The presence of noise points suggests some individuals are isolated or not part of larger groups. *Frame 50:* Like Frame 10, there are multiple clusters, but the distribution might be slightly different, indicating movement or changes in the crowd's formation over time. *Frame 100:* This frame also shows distinct clusters with some noise points, indicating a consistent pattern of crowd grouping.

These visualizations provide insights into how people were grouped or dispersed in the crowd. The parameters of DBSCAN (epsilon and minimum samples) were chosen to demonstrate the algorithm's capability but can be adjusted for more refined analysis.

TABLE VII
CLUSTERING RESULTS FOR EACH FRAME

Total Frames	Average Clusters Frame	Proportion Outliers
336	40.595	0.0298

Table 7 shows the clustering results for each frame, including the proportion of outliers. It reveals that cluster numbers and distributions vary over time, reflecting people's movements and group dynamics. About 2.98% of data points were outliers, lacking nearby neighbors as per DBSCAN. On average, there were 40.6 clusters per frame. These insights can help identify hazardous areas based on people's collective behavior at certain times and places.

IV. Conclusion

Exploring the use of deep learning in ensuring crowd safety, particularly in the context of preventing crowd collapses, represents a significant and innovative direction for future research. Deep learning, a subset of machine learning that uses algorithms inspired by the structure and function of the brain called artificial neural networks, has shown remarkable success in various domains such as image and speech recognition, natural language processing, and autonomous driving. Applying these techniques to crowd safety could open new avenues for preventing tragedies during large gatherings.

One promising approach could be the integration of density-based spatial clustering of applications with noise (DBSCAN), a popular clustering algorithm, with deep learning techniques. DBSCAN excels in identifying high-density areas and outliers in spatial data, which can be crucial in crowd analysis. By integrating DBSCAN with deep learning models, it might be possible to analyze complex crowd dynamics more effectively.

Such an integrated system could process data from various sources like surveillance cameras, drone footage, and mobile device signals. Deep learning models, trained on vast datasets of crowd movements and patterns, could identify potential risks of crowd collapses or dangerous bottlenecks in real-time. The system could analyze factors such as crowd density, flow dynamics, and individual behaviors to detect anomalies or dangerous situations.

The use of DBSCAN in this context could help in accurately segmenting different clusters within a crowd. For instance, it could differentiate between a densely packed, but stationary group and a rapidly moving cluster, each posing different types of risks. By recognizing these patterns, the system could provide early warnings to event organizers, security personnel, and local authorities, enabling them to take proactive measures to prevent accidents.

Moreover, integrating deep learning with crowd safety applications could lead to the development of predictive models. These models could learn from past incidents of crowd collapses and identify early warning signs, potentially preventing accidents before they occur. They could also be used in planning and simulation tools to design safer public spaces and event venues.

Further research in this area could also explore the ethical and privacy implications of using such technology. Ensuring that crowd monitoring respects individual privacy and does not lead to unwarranted surveillance is crucial. Additionally, there is a need for robust and transparent models that can be trusted and understood by the public and authorities.

In conclusion, leveraging deep learning and algorithms like DBSCAN for enhancing crowd safety presents a fascinating and potentially lifesaving field of research. It combines advanced technological solutions with a profound societal impact, aiming to protect people in public spaces and at large events. As with any advanced technology, its development and deployment must be handled responsibly, with attention to ethical considerations and societal impacts.

Acknowledgment

The Basic Science Research Program supported this research through the National Research Foundation of Korea (NRF), funded by the Ministry of Education (No.2020R1A6A1A03040583). Additionally, this work was supported by the Basic Science Research Program through the

National Research Foundation of Korea (NRF), funded by the Ministry of Education (RS202300247355).

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