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Artificial Intelligence in Crowd Disaster Management: A Comprehensive Review of Technologies, Applications, and Future Directions

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Abstract— *Large crowds—such as those at religious events, concerts, or sporting venues—are prone to risks of crowd disasters including stampedes, panic-induced chaos, and congestion-related incidents, which constitute serious threats to public safety. Real-time monitoring, predictive analysis, and timely decision-making are key requirements for effective crowd disaster management to minimize risk and improve safety measures. In this field, Artificial Intelligence (AI) has emerged as a powerful solution, utilizing advanced technologies including machine learning, computer vision, and simulation models to assess and control crowd behaviour efficiently. This paper reviews the application of AI in crowd disaster management, including risk assessment, anomaly detection, evacuation planning, and emergency response. Live video feeds are analysed by AI-powered surveillance systems, which also predict potential hazards based on movement patterns. Through IoT devices, data can be instantly processed, enabling dynamic evacuation routing through knowledge-based evacuation systems. Robotic and drone technology combined with AI ensures that emergency responders can respond to situations as they unfold. Beyond disaster prevention, AI in crowd management improves emergency management processes and resource utilization. The role of AI is discussed in this paper, leading to the finding that it can improve safety, make evacuations more efficient, and reduce loss of life. By utilizing AI-driven intelligent systems, authorities can significantly enhance crowd control measures, creating safer and more organized environments for large gatherings.*

Keywords— Crowd Management, Disaster, Artificial Intelligence, Stampede, Safety, Strategies.

I. INTRODUCTION

Globally, crowd disasters—namely stampedes, crushes, and attendant panic—have over the years caused heavy loss of human life and material damage. Such risks can only be mitigated if public safety can be assured in densely populated areas such as stadiums, religious gatherings, concerts, and urban events [1]. With predictive analytics, real-time monitoring, and automated decision-making, Artificial Intelligence (AI) has emerged as a powerful tool for disaster management to prevent and control crowd-related incidents. Situational awareness through AI-driven technologies, specifically computer vision, machine learning, and simulation models, enables crowd behaviour analysis, detection of anomalies, and prediction of hazards. From live footage, surveillance systems using AI recognize overcrowding, while predictive algorithms assess risks and recommend preventive measures. Drones and robots powered by AI can assist during emergencies to help evacuate people quickly. This paper examines the role of AI in crowd disaster management—including risk assessment, early warning systems, and crisis response applications. Based on these insights, authorities can improve crowd control strategies, evacuation procedures, and minimize casualties. The integration of AI in disaster management offers a revolutionary approach to public safety, ensuring safe and regulated large assemblies through data-driven intelligent solutions.

II. CROWD BEHAVIOUR

2.1 Theoretical Foundations:

Turner and Killian's Emergent Norm Theory (1957) and Institutional Amnesia Theory exist to explain the behaviour of crowds in the context of religious gatherings [2]. Collective rituals play a role in helping individuals develop unity and a sense of personal identity. This includes certain ways of acting that bypass the need for individual assessment. This aligns with Helbing et al., who explain that when people feel unsafe in a crowd, they may prioritize their thoughts and feelings above all else, rather than focusing on self-preservation [3]. This suggests that ongoing failures in crowd management stem from organizations tending to forget past mistakes [2]. Boin and Schulman (2008) explain that frequent governance failures arise from entrenched bureaucratic habits, progressive institutional memory gaps, and primarily from failing to apply lessons learned from past experiences. This idea is further supported by investigations of crowd disasters, where reforms are often implemented after a disaster occurs but fail to have lasting impact [4].

2.2 Religious Gatherings and Empirical Studies on Stampedes:

Scholars have studied crowd disasters at religious gatherings, establishing that high crowd density can trigger stampedes. Research indicates that when more than six persons per square meter are present in enclosed areas, the risk of a crush increases due to shockwaves, as evidenced during the 2015 Hajj stampede. Similar patterns have been documented at Hindu places of worship. According to findings by G. et al. (2017), 78% of global stampedes occurred at sacred locations such as riversides and hills. These incidents often occur when self-preservation overrides planned evacuation protocols. The Indian Institute of Science estimated that devotion during the Kumbh festival caused a 34% surge in crowd density, leading to pedestrians moving at higher speeds during peak hours [3].

2.3 Historical Instances and Governance Catastrophes:

Analysts have identified that administrative negligence and elite-focused security arrangements were major contributing factors to disasters at Kumbh Mela festivals in the past. Inadequate police presence during the Allahabad stampede of 1954 exacerbated the situation [4]. Critical routes were under-policed while priority was given to protecting VIPs. Similarly, in 2025, officials again found that unmanned barricades had been placed in high-risk areas during ministerial visits. The crowd management approaches described in Maclean's work "Pilgrimage and Power" reflect colonial methods of crowd control [5]. These strategies prioritized protecting state officials rather than ensuring pilgrim safety. Historical records indicate that marginalized pilgrims using less prominent entrances were more likely to die in pre-independence stampedes, a pattern that continues in modern data [6].

2.4 Interventions and Limitations in Technology:

Advances have been made in using machine learning for crowd surveillance to prevent risk incidents. AI-powered crowd surveillance systems trained on CCTV footage operate primarily at night. These systems can predict dangerous crowd densities (≥ 8 persons/m^2) with reasonable accuracy [5]. However, current systems sometimes misclassify devotional urgency as anomalous behaviour, triggering false alarms [7]. Research incorporating ritualistic behaviour into simulation models has improved accuracy; the ECDS-ED2L model, which includes religious behavioural parameters, demonstrated that crowd velocity peaks at 58% during specific ritual periods, including the day of Mauni Amavasya [4]. Institutional resistance remains a significant challenge, with 70% of Kumbh 2025 safety officers expressing skepticism that AI-based risk analysis aligned with conventional crowd management wisdom [4].

2.5 Natural Language Processing in Disaster Inquiry Analysis:

Natural Language Processing (NLP) applied to official inquiry reports reveals important patterns. Analysis of past Kumbh Mela stampede reviews shows that unforeseen surge and crowd management issues have been consistently documented over many years, yet institutional accountability remains unaddressed [8].

2.6 Systemic Vulnerabilities: Determinants of Risk:

Scholars studying religious disasters argue that stampedes result from pilgrimage organizational structures rather than solely leadership failures. Singh's theory of "Necro-politics of Devotion" posits that devotees accept significant risks as spiritually meaningful sacrifices [6]. Computational theology models suggest that during critical religious periods, devotees prioritize ritual completion 3.2 times more than personal survival [3].

2.7 Bridging the Gap: Contributions of This Study:

Existing literature tends to segment technical crowd modelling from ethnographic disaster studies. This study bridges these approaches through:

- Temporal synthesis correlating real-time sensor data from the 2025 Kumbh Mela with historical archival data, including 1954 stampede reports
- Extension of devotional metrics into the Crowd Risk Index (CRI) framework, enhancing predictive accuracy in deep learning simulations
- Examination of how AI systems might create complex information ecologies that both pose risks and offer opportunities for organizational learning

This research challenges the framing of stampedes as algorithmically predictable events divorced from institutional accountability. It advocates for rethinking governance failures as systemic rather than situational, and for integrating crowd science with historical and ethical perspectives.

III. IOT EVACUATION PLANNING SYSTEM

The integration of IoT and AI has transformed traditional crowd disaster management, making evacuation planning more efficient and rapid. IoT supports emergency response systems by ensuring continuous sensor connectivity and real-time data access. When AI analytics are applied to this data, authorities gain improved situational awareness and can take necessary actions quickly during emergencies. In an evacuation planning system, IoT devices are distributed to detect crowd concentrations, movement directions, and environmental hazards. Information flows continuously to central processors, where AI analyzes it for potential threats and identifies optimal evacuation routes. AI's ability to adjust routes in real time ensures that people are not slowed or trapped in crowded areas near danger.

The combination of IoT and AI reduces response time significantly. During intense situations, traditional evacuation planning using fixed routes and manual coordination often proves inadequate. In contrast, AI-supported systems can rapidly assess fire conditions, structural integrity, and crowd distributions to suggest optimal evacuation routes as events unfold. Additionally, these systems help prevent panic and confusion during emergencies. First responders and authorities can coordinate evacuation strategies using continuously updated AI-driven analytics, benefiting all stakeholders [9].

IV. PREDICTION

Prediction involves mathematical models designed to identify patterns in data, analyzing current and historical data to forecast future actions and trends. This section reviews existing literature and presents analysis and comparison of contributions, beginning with a brief discussion of how social media and AI contribute to disaster prediction.

4.1 Social Media Prediction:

While numerous social media platforms exist, this analysis focuses on social networks, as comprehensive coverage of all platforms would be impractical for disaster management applications. Researchers studying two Chinese earthquakes developed a formal model for Weibo data to investigate information diffusion during seismic events [18]. Their findings demonstrated that human actions in crises can be studied using online social media data, providing authorities with valuable insights into behavioural patterns during emergencies.

Business systems commonly use crowd feedback through social media platforms to predict brand performance and guide decisions. Research has developed methods for predicting emotional responses by processing Twitter data [19]. Emotions are displayed in real time using various AI-supported techniques. Like Weibo, Twitter can be used to predict emergencies and natural disasters, as people's reactions to such events manifest distinct patterns on these platforms.

Recent work has incorporated online text data into established crowd movement forecasting models, including data on rare, non-recurring events [20]. Because Twitter disseminates information faster than traditional media, tweets are included in models to capture non-recurring crowd behaviours that influence data movement [21]. Similarly, research utilizing crowdsensing on Weibo enables rapid detection of unexpected events [22]. This approach requires identifying sensors that can locate tweets containing useful information during emergencies.

Processing Twitter streams for crisis management necessitates unsupervised domain adaptation and multi-task learning before making predictions [23]. These techniques address challenges of limited and unlabeled data, with demonstrated performance despite data scarcity. Semi-supervised learning using iterative random forest fitting enables prediction of event popularity based on hashtag combinations across multiple messages [24]. This research introduced novel methods for incorporating hashtag influence into event popularity prediction.

Beyond popularity, rumors on social media significantly influence information dissemination. Anxiety and fear can spread rapidly when rumors circulate during crises. Research using RCNN to forecast rumor propagation on Twitter, validated on two Weibo emergency rumor datasets from different provinces, demonstrated strong predictive performance [25].

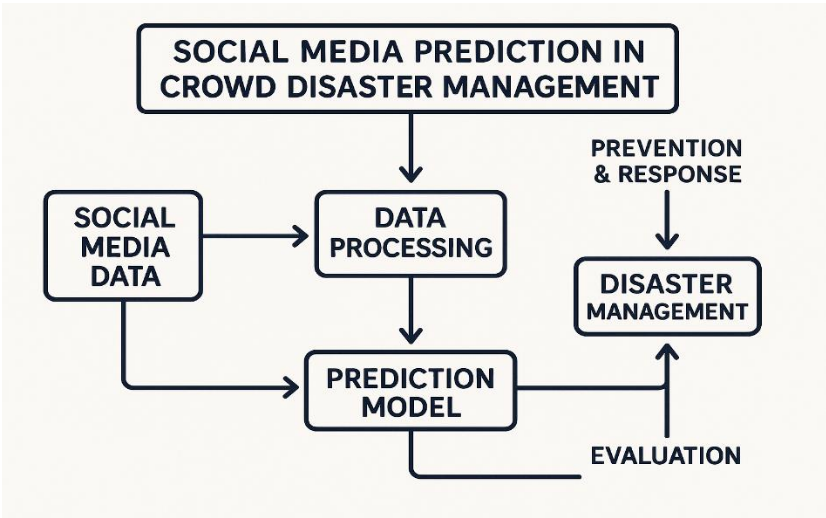

FIGURE 1: Model of Social Media Prediction in Crowd Disaster Management

4.2 Artificial Intelligence Prediction:

Understanding human and vehicle movement patterns in urban environments is essential for applications such as emergency evacuation and rescue. This section examines AI technologies for predicting crowd movements, facilitating emergency response.

Congestion Forecasting: Research developing methods for predicting crowd density and movement patterns has created new human mobility datasets from real-world smartphone applications [26]. Using convolutional LSTM neural networks with pyramid-shaped models and high-dimensional attention mechanisms, Deep Crowd—a novel deep learning tool for crowd analysis—has been developed. Multi-relational graph convolutional gate recurrent unit models for urban crowd density prediction have demonstrated superior performance when incorporating spatiotemporal information [27].

The ConvLSTM-Att model (1DCNN-LSTM-Attention), a deep learning approach for crowd flow inference combining CNN and ConvLSTM-based networks, preserves geographical details while analyzing sequential data [28]. The attention mechanism identifies significant crowd motion changes beyond what recurrent modules alone can detect. Crowd VAS-Net, a framework focusing on crowd mobility, examines saliency, acceleration, and velocity in video frames [29]. Using DCNN, Crowd VAS-Net evaluates crowd normality by considering movement and appearance patterns, with extracted features classified using random forest algorithms.

LSTM networks have been employed to develop pedestrian trajectory prediction models incorporating average speed and directional vehicle counts for each participant [30]. Congestion control early warning systems combining object recognition and tracking have been developed, using R-CNN architecture with pre-trained CNN Google Inception models for congestion prediction, followed by object tracking systems to detect anomalous crowd behaviour that might indicate impending disasters [31].

Support vector regression with online sequential learning has been proposed for simplified prediction in dense crowd scenarios, though applicability to all crowd types remains limited [32]. Analysis of inter-regional travel patterns and residential distributions enables origin-destination flow forecasting and transportation planning [33].

Healthcare Applications: Overcrowding in hospital emergency departments poses public health challenges, and accurate patient flow prediction improves departmental efficiency and care quality [34]. Deep learning systems monitoring patient admissions, treatments, and discharges in triage zones enable emergency room activity forecasting. Post-surgical hospitalization requirement prediction using electronic health record data from emergency visits, combined with convolutional neural networks, has demonstrated high accuracy when data are converted to image formats [35].

Natural Disaster Prediction: Earthquake intensity prediction models incorporating transportation system damage data from the past two decades, combined with data mining and AI techniques including KNN, SVM, logistic regression, and decision tree algorithms, enable earthquake forecasting based on transportation system damage characteristics [36]. Structural recurrent neural networks addressing temporal and geographical earthquake patterns have improved forecast accuracy [37].

Flood prediction models tracking humidity, temperature, pressure, rainfall, and river water levels to determine temporal relationships have been developed [38]. Typhoon disaster management frameworks for electric power networks incorporate wind damage warning systems for transmission lines [39]. Hybrid prediction models combining extreme value type 1 probability distributions with Monte Carlo methods and random forests assess transmission line damage probability during typhoons [40].

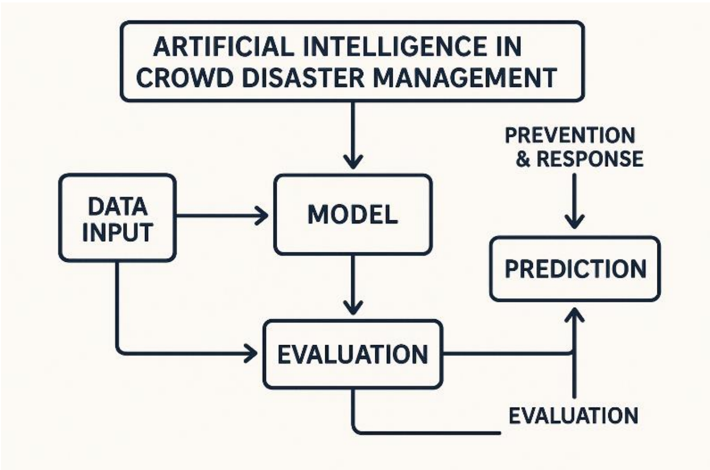

FIGURE 2: Model of AI in Crowd Disaster Management

V. REAL TIME MONITORING

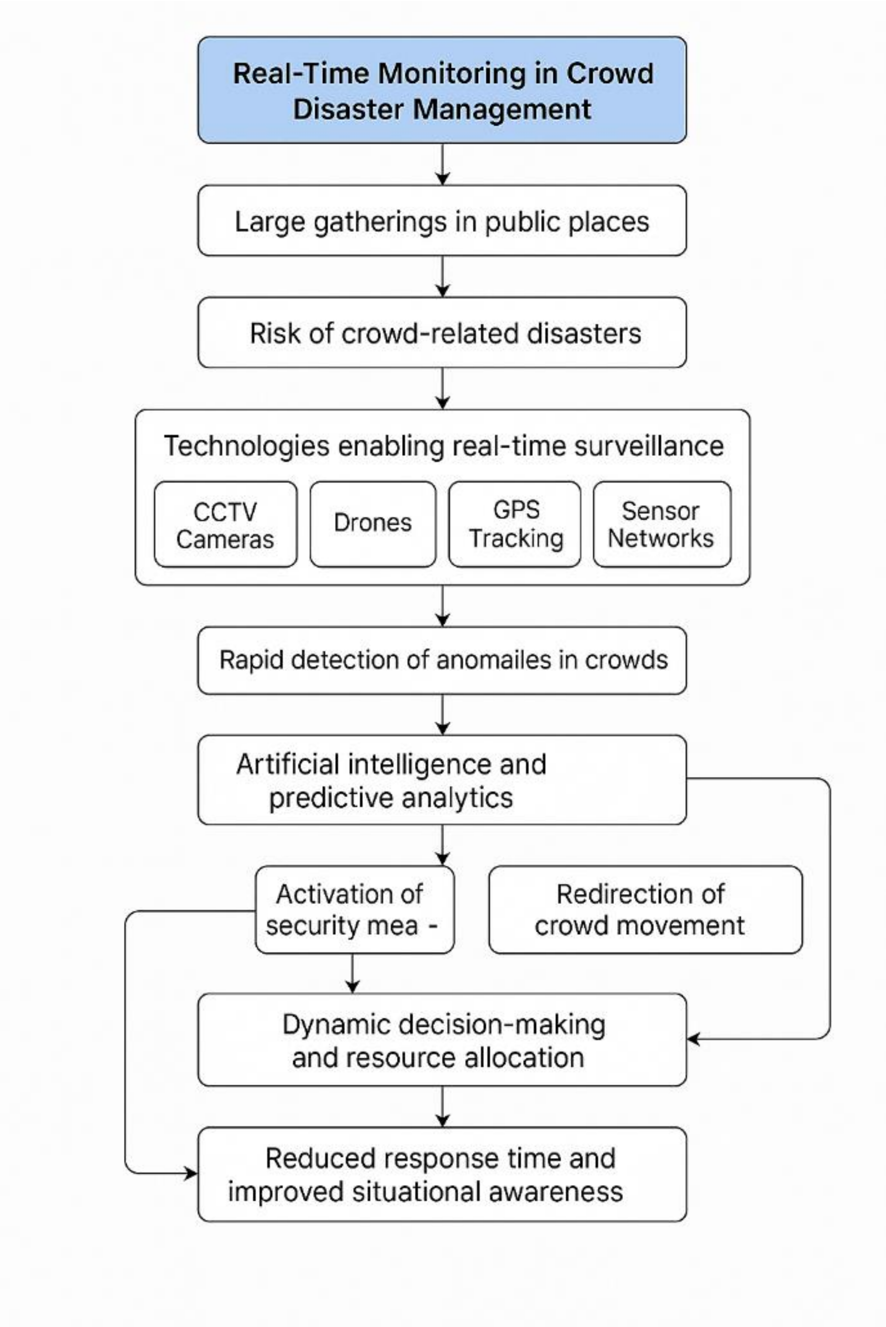

FIGURE 3: Real Time Monitoring in Crowd Management

Real-time monitoring is essential for effective crowd disaster management, enabling authorities to observe, analyze, and respond to dynamic crowd conditions as they unfold. The risk of crowd-related disasters—including stampedes, crushes, and panic-related incidents—has increased significantly with growing attendance at public gatherings such as concerts, festivals, sporting events, and religious pilgrimages. Technologies including CCTV cameras, drones, GPS tracking, and sensor networks enable real-time surveillance and rapid anomaly detection in large crowds. These systems provide data on crowding density, movement patterns, and congestion hotspots, which artificial intelligence and predictive analytics use to estimate potential future risks.

For example, sudden changes in crowd flow or unexpected concentrations in specific areas can trigger alerts, prompting security personnel to intervene or redirect crowd movement through public announcements or barriers. Real-time monitoring also facilitates better coordination among emergency services, event organizers, and local authorities, enabling dynamic decision-making and resource allocation—such as dispatching medical aid to specific zones or adjusting entry and exit routes to prevent bottlenecks.

Integration with mobile applications and social media platforms for information dissemination enables rapid communication with broad audiences, directing people to safer locations and minimizing panic. In disaster scenarios, every second counts. Real-time monitoring significantly reduces response times and improves situational awareness, potentially saving lives and preventing chaos. This approach transforms crowd management from reactive to proactive discipline by establishing continuous feedback loops between crowds and decision-makers.

VI. AI-POWERED DECISION MAKING

Internet of Things (IoT) devices are increasingly analyzed by Artificial Intelligence (AI) to predict crowd behaviour and detect potential hazards in real time. These devices collect data from surveillance cameras, motion sensors, smartphones, and wearables—providing information on crowd density, patterns, and environmental conditions. AI processes this data to predict crowd movements, identify potential congestion points, and assess safety risks.

Machine learning models are essential in this process, integrating historical and real-time data to determine optimal evacuation pathways for various scenarios. These models identify patterns from past incidents combined with live updates to predict crowd behaviour under different conditions, enabling authorities and emergency planners to make informed decisions about traffic management to minimize panic and ensure safety.

Predictive evacuation planning represents one of the most critical applications of this technology. Crowd-driven analytics can continuously calculate the safest and most efficient evacuation routes based on current crowd conditions. Updates can be disseminated through mobile applications, public address systems, or digital signage to guide people away from danger. By combining IoT data with AI prediction capabilities, crowd disaster management becomes more proactive and responsive, improving situational awareness and enhancing safety and efficiency during emergencies.

VII. SMART EVACUATION GUIDANCE

The University of Illinois Urbana-Champaign (UIUC) utilizes IoT-enabled smart systems to ensure public safety and provide effective guidance during emergency evacuations. These advanced systems rely on real-time data to deliver dynamic instructions to crowds, ensuring efficient and orderly movement toward the safest exits. Multiple communication channels—including digital signboards, mobile notifications, and voice assistant alerts—disseminate information across the campus.

Integration of Artificial Intelligence (AI) with IoT infrastructure enables more intelligent and personalized evacuation planning. These systems interface with personal smart devices (smartphones, wearables), collecting real-time location and environmental data to provide targeted evacuation route recommendations. This personalization accounts for surrounding crowd density, blocked pathways, and changing threat conditions, providing each individual with optimal escape routes.

During crises, such intelligent systems dramatically reduce response time and minimize confusion and congestion. By combining IoT sensing capabilities with AI decision-making, emergency response becomes faster, more efficient, and better adapted to individual needs. This represents a proactive step toward more intelligent and secure environments in the digital age.

VIII. AUTONOMOUS ASSISTANCE AND ROBOTICS

In large-scale disaster situations, drones and robotic systems powered by Internet of Things (IoT) technologies play crucial roles in strengthening evacuation efforts and saving lives. Artificial Intelligence (AI) integrated with these technologies enables immediate support during emergencies. Drones can be rapidly deployed to provide aerial views of affected areas, offering comprehensive situational awareness. Equipped with cameras and environmental sensors, they capture real-time footage and transmit data to emergency responders, enabling faster assessment and more informed decision-making.

AI-driven drones can identify congested areas, detect structural damage, and locate people in distress. This information is essential for organizing rescue efforts and adjusting evacuation routes as situations evolve. Robotic assistants similarly contribute to ground support in hazardous or inaccessible areas. These robots can guide people to safe exits, deliver emergency supplies, or assist in rescuing trapped individuals.

The combination of AI, IoT, and autonomous mobility in drones and robots significantly advances disaster response operations, improving efficiency, safety, and precision. Their ability to operate in dangerous zones reduces risks for human responders and accelerates access to critical areas, ultimately improving evacuation outcomes.

IX. INTEGRATION WITH EMERGENCY SERVICES

IoT-based evacuation planning systems have transformed emergency management by enabling seamless coordination among multiple agencies—emergency responders, law enforcement, and healthcare providers. These systems collect real-time data from sensors deployed throughout public spaces, buildings, and infrastructure, including crowd density, movement patterns, environmental conditions, and potential hazards.

AI-driven command centers analyze incoming data instantaneously, using machine learning algorithms to assess emergency severity and scope, and efficiently allocate critical resources. AI can automatically dispatch medical teams, redirect authorities, and coordinate security responses. Automated emergency alarm systems notify relevant authorities immediately upon crisis detection, providing precise location data, emergency nature, and potential escalation risks.

Without such coordination, emergency response suffers from delays and inefficiencies that can cost lives. The integration of IoT and AI creates a comprehensive framework for enhanced disaster preparedness and response, enabling more coordinated evacuations and ultimately protecting more lives.

X. CASE STUDIES

10.1 Case Study 1: Kumbh Mela, Prayagraj, 2025

The Kumbh Mela 2025 held at Prayagraj experienced a massive religious gathering that revealed significant stampede risks due to overcrowding. Key issues reported included weak barricading, congested roads, collapsed shelters, blocked emergency exits, poor sanitation, and water depletion. Frequent waste disposal, sewage flow, and mass rituals near riverbanks increased biological contamination, with E. coli and other pathogens detected in river water [41]. The stampede resulted in numerous health hazards and loss of life among pilgrims.

10.2 Case Study 2: Sabarimala, Kerala, 2016

Sabarimala, a sacred site in Kerala, South India, attracts over 30 million devotees within a 41-day period when the temple is open to pilgrims. Mass gathering challenges include crowd stampedes, human crushes, and communicable disease transmission risks. Medical personnel faced coordination difficulties and limited access to paramedical support. Data were collected using modified health risk ranking methods including Risk Prioritization Index (RPI), Likelihood Level Index (LLI), and Corresponding Consequences Level Index (CLI) to establish risk rankings [42].

10.3 Case Study 3: Antananarivo, Madagascar Stampede, 2019

An incident at Antananarivo, Madagascar in 2019 resulted in 16 deaths and numerous injuries during a human crush at Mahamasina Municipal Stadium before a concert [43]. The stampede occurred when a large crowd gathered for a concert following the national Independence Day military parade. As the show was about to begin, the crowd surged toward the entrance, and police closure of entry points created a pile-up situation resulting in casualties.

10.4 Case Study 4: Hajj in Mecca, Saudi Arabia, 2015

Hajj, an annual religious gathering attracting approximately 3 million pilgrims from over 140 countries to Mecca, Saudi Arabia, presents significant safety challenges. Stampedes and overcrowding have caused thousands of deaths over the years [44]. Radio Frequency Identification (RFID) wristbands are now used to count pilgrims at mosque entrances, complemented by Community Response Grids (CGRs)—networked approaches to risk communication integrating pilgrim voices through social media channels [45].

10.5 Case Study 5: Vaishno Devi Temple Stampede, Jammu and Kashmir, 2022

Vaishno Devi Temple, a popular religious shrine in Jammu and Kashmir, experienced a crowd disaster on January 1, 2022 at Gate No. 3, resulting in 15 injuries and 12 deaths [46]. The incident was caused by sudden crowding within limited space, absence of emergency exits, lack of coordination, and restlessness among devotees, creating a stampede with severe casualties.

XI. RECOMMENDATIONS

11.1 AI-Driven Monitoring and Observation:

Leverage integrated AI technology combining CCTV, drone video feeds, and IoT sensors (density sensors, wearables) for real-time mapping of crowd densities, movement, and anomalies. Employ computer vision algorithms trained in religious and cultural contexts (e.g., ritual behaviours during Kumbh Mela) to reduce false alarms and enhance predictive accuracy for surges. Utilize thermal imaging for nighttime surveillance and congestion warnings at thresholds ≥6 persons/m².

11.2 Predictive Risk Analytics:

Develop a Python-based Crowd Risk Index (CRI) combining AI-based simulations with devotional indicators (ritual pressure, sacred paths) and historical disaster records. Employ spatiotemporal models (ConvLSTM-Attention networks) for forecasting density peaks and stampede risks. Incorporate social media analytics (Twitter, Weibo) and NLP for identifying panic signals and rumour trends for early warnings.

11.3 Dynamic Evacuation Systems:

Integrate IoT sensor networks and AI to provide real-time evacuation routing. Use mobile apps, digital signage, and voice assistants to guide people along emergency routes dynamically adjusted for congestion, blocked exits, or hazards. Integrate RFID/GPS into pilgrim wearable technology for tracking and family reunification during emergencies.

11.4 Robotics and Autonomous Response:

Deploy AI-guided drones for aerial surveillance, damage assessment, and medical supply delivery to inaccessible areas. Deploy ground robots to clear rubble, deliver emergency equipment, and guide trapped individuals through optimal routes.

11.5 Emergency Service Integration:

Develop AI command centers combining surveillance, forecasting, and ground unit (police, medical) intelligence. Automate resource deployment (e.g., dispatching ambulances to danger zones) and utilize blockchain for secure real-time information sharing among agencies.

11.6 Governance and Training:

Address institutional resistance through AI-based training simulating disaster scenarios (e.g., stampedes on riverbanks during ritual festivals). Use NLP analysis of past inquiry reports (e.g., Kumbh Mela 1954/2025) to identify systemic weaknesses and update procedures. Mandate AI adoption in crowd management policy with ethical audits to prevent algorithmic bias.

11.7 Case Study Deployments:

For religious events (e.g., Hajj, Kumbh), employ CRI with ritual-calibrated sensors and multi-language alert systems. For event venues (e.g., stadiums), employ crowd flow prediction (Deep Crowd models) and AI-controlled barricades to manage entry/exit bottlenecks. Post-disaster, utilize NLP on incident reports to ensure accountability.

11.8 Key Technologies:

Focus on edge computing for low-latency processing, federated learning to protect crowd data privacy, and multi-agent systems for autonomous robot and drone coordination. Cross-validate models on diverse datasets (e.g., Sabarimala health indices, Mecca RFID traces).

XII. CONCLUSION AND FUTURE WORKS

Advanced technologies comprising sensing, Internet of Things (IoT), social media (SM), big data analytics, and artificial intelligence (AI) have the potential to significantly reduce casualties and infrastructure loss during natural or human-made disasters. This survey examines the development of SM and AI-based solutions for prediction, detection, response, and emergency management, providing a comprehensive overview of existing disaster management technologies and assessing their effectiveness in disaster scenarios. Each approach is systematically categorized and evaluated using various performance metrics.

While these technologies offer significant benefits—including faster response times, improved situational awareness, and better resource allocation—substantial challenges remain in their implementation, including data reliability, scalability, real-time decision-making, and ethical considerations. Overcoming these limitations requires continued research and development.

12.1 Micro Blogging System:

Beyond improving accuracy and precision in detecting relevant messages, AI-based emergency management models face additional challenges. Most existing SM crowd management research relies primarily on Twitter as a data source. Information synchronization and response patterns may differ across platforms, and some platforms like Facebook restrict data extraction. Incorporating diverse SM platforms, considering varying data quality across platforms, remains an open challenge. Data type and quality may vary significantly based on typical user demographics for each platform.

12.2 User Participation:

Effective crowdsourcing, big data, and SM applications require high levels of user engagement. While incentives can encourage participation, research suggests that users may not require additional motivation to engage in socially beneficial collective actions [47]. Questions regarding optimal incentive quantity and quality have been partially addressed in literature but require further investigation.

12.3 Individual Privacy:

Public safety during emergencies must be balanced against individual privacy rights to protect the dignity and wellbeing of affected populations. Disaster management sometimes requires collection of personal and sensitive information to support rescue and recovery operations. Such data raises privacy and security concerns regarding potential misuse or unauthorized access. Ensuring that information collected from crisis zones remains protected from malicious actors is essential. Balancing privacy protection with effective emergency response presents significant challenges requiring careful examination and optimization of the privacy-efficiency trade-off. Each scenario must be evaluated individually to design systems achieving optimal balance between efficiency and privacy protection. Continued research is needed to develop secure, adaptive frameworks supporting both public safety and data protection in crisis situations.

12.4 Cost Reduction:

Global researchers are working to reduce equipment and software deployment costs for disaster management technologies while maintaining or improving system performance. Given that emergency systems may remain idle for extended periods but must perform reliably during rare critical events, questions about cost-effectiveness arise. Developing methods to utilize emergency equipment during non-emergency periods without compromising emergency response capabilities represents an important research direction.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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