



REVIEW

Human Behaviour Classification in Emergency Situations Using Machine Learning with Multimodal Data: A Systematic Review (2020–2025)

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ABSTRACT: With growing urban areas, the climate continues to change as a result of growing populations, and hence, the demand for better emergency response systems has become more important than ever. Human Behaviour Classification (HBC) systems have started to play a vital role by analysing data from different sources to detect signs of emergencies. These systems are being used in many critical areas like healthcare, public safety, and disaster management to improve response time and to prepare ahead of time. But detecting human behaviour in such stressful conditions is not simple; it often comes with noisy data, missing information, and the need to react in real time. This review takes a deeper look at HBC research published between 2020 and 2025 and aims to answer five specific research questions. These questions cover the types of emergencies discussed in the literature, the datasets and sensors used, the effectiveness of machine learning (ML) and deep learning (DL) models, and the limitations that still exist in this field. We explored 120 papers that used different types of datasets, some were based on sensor data, others on social media, and a few used hybrid approaches. Commonly used models included CNNs, LSTMs, and reinforcement learning methods to identify behaviours. Though a lot of progress has been made, the review found ongoing issues in combining sensors properly, reacting fast enough, and using more diverse datasets. Overall, from the findings we observed, the focus should be on building systems that use multiple sensors together, gather real-time data on a large scale, and produce results that are easier to interpret. Proper attention to privacy and ethical concerns needs to be addressed as well.

KEYWORDS: Human behaviour Classification (HBC); public safety; multimodal datasets; privacy concerns; missing information; multi-sensor integration; healthcare

1 Introduction

As time passes and the population is continuously rising and ageing, various challenges like urban growth, climate change, and unpredictable geopolitical conditions are paving the way for emergencies to happen more often. Because of this, the need for fast, responsive, and human-centred management systems is becoming more critical than ever. Defined formally, HBC is an automatic process for the identification and categorisation of human activities and their behavioural patterns based on data from sensors, video, or multimodal sources in order to support decision-making in real-world scenarios. In this study, HBC is specifically used for emergencies, which cover activities such as fall detection, running, crouching, reactions



during panic, and evacuation movements in case of disaster. HBC systems are helpful tools that can connect real-life incidents with timely and targeted actions. These systems detect behaviour patterns by processing data from various sources that may lead to or indicate emergency conditions [1,2]. This is the reason why HBC is now being applied in many areas such as healthcare, surveillance, public safety, assisted living, environmental monitoring, and evacuation strategies [3].

As this need becomes stronger, the role of HBC systems becomes more visible and essential, and because of that, it becomes important to explore how exactly these systems function and what kind of situations they are meant to address. When we deeply understand their core workings, their role in emergency response becomes even more convincing and impactful. To assume the understanding of human behaviour in such emergencies, the use of intelligence-based systems is important [4]. HBC systems have become vital tools to address these issues. For example, ref. [5] detected leg postural abnormalities, which can be helpful to identify people with such abnormalities during any emergency, so that the required response can be generated that could save lives. These calamities can refer to personal incidents, such as falls (natural or deliberate) and sudden health concerns [6,7], as well as large-scale disasters, such as fires, earthquakes, and even terrorist attacks [8,9]. An important contribution of this review is the identification and analysis of multimodal sensing frameworks. Datasets like KFall, which combine inertial data with synchronised video, are excellent examples of multimodal input sources designed to improve both accuracy and interpretability [10]. These datasets combine inputs such as RGB video, thermal imaging, inertial data from wearables, physiological signals, environmental measurements, and contextual data. The integration of these modalities not only improves accuracy but also provides robustness to missing or degraded data, a common issue in real-world emergency scenarios [1].

As the world becomes more complex and unpredictable, it has become the need of the time to recognise and respond to emergencies more effectively and logically than ever [11]. This supports public safety, strengthens healthcare systems, and increases the level of preparedness for such calamities [12]. By accepting the importance of timely detection and response, it becomes essential to understand how the systems are built and what types of data they need to work on. Their importance is often dependent on the variety and richness of the information they can process. Comparing data from various sources such as visual, auditory, physiological, inertial, and environmental sensors [2,6,8,9,10]. HBC systems have greatly improved their ability to quickly recognise and efficiently respond during emergencies, giving more accurate interpretations [13]. On the other hand, single-sensor systems that rely only on visual or motion data tend to be less robust and computationally heavy, depending on the quality of images or video used [3,9]. For example, vision-based fall detection often fails under poor lighting or occlusions [14], whereas inertial-sensor-based systems may misclassify rapid but harmless movements [8,15]. Multimodal approaches combining both (through different levels of modality fusion as shown in Fig. 1) tend to reduce such errors [16]. They often lack context awareness and struggle to adapt across different situations. Multimodal systems, however, bring together diverse data inputs to form a more complete and reliable understanding and prediction of human actions and intent [17]. Between the single-sensor and multimodal systems, the difference clearly illustrates how much potential lies in combining data streams.

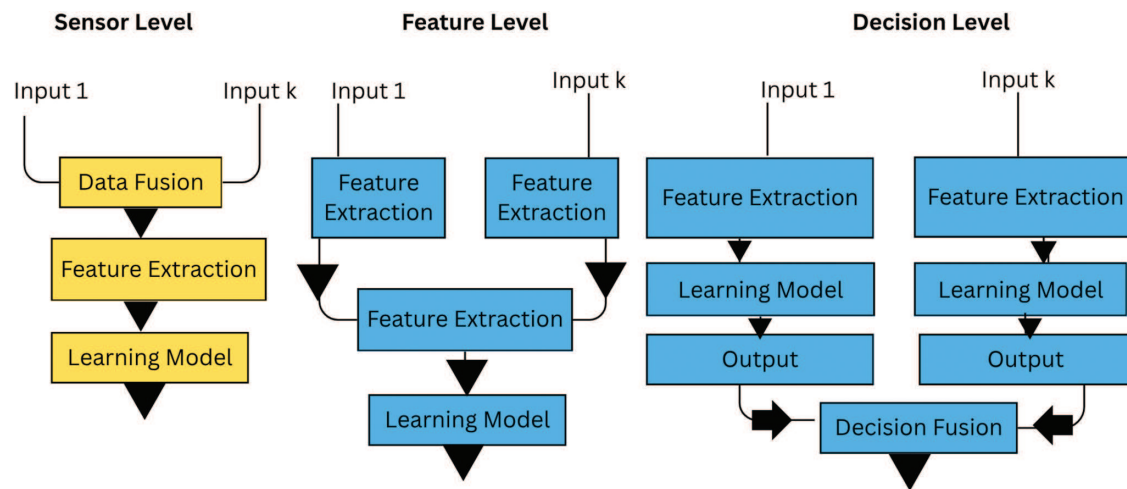


Figure 1: An overview of different levels of modalities fusion as described in [16]

This study explores how researchers have employed state-of-the-art architectures to overcome the limitations of traditional ML models. Various smart techniques like convolutional neural networks (CNNs) [6], LSTMs [8], BiLSTMs and attention mechanisms [13] have been explored to check their success in recognising behaviour during emergencies. Each of these methods is tested for how well it handles mixed data sources and performs in real-world conditions. When these systems are actually used in emergencies, they bring extra challenges [9].

The model must not only work well, but it also needs to respect human values, social norms, and ethical boundaries. As movement analysis for determining behavioural patterns has raised privacy concerns when relying on continuous video monitoring [1]. Wearable-based systems are often preferred due to their less intrusive nature [18]. A single missed signal or a false alert can lead to serious outcomes in any emergency [19]. That's why it's not just about accuracy anymore; we also need systems that can clearly explain why they acted a certain way, especially when lives are on the line. Another important aspect is how well these systems behave in different situations, like with different people, changing surroundings, and unpredictable conditions. To build genuine trust and ensure that practices remain responsible, privacy-first measures have to be part of the design right from the beginning. Methods like on-device processing, anonymising data and even federated learning should not be treated as optional add-ons but as necessary ethical requirements [20]. By including these safeguards in the core, we can ensure that systems not only work intelligently but also remain accountable and responsible when applied in real-world settings.

While human activity recognition (HAR) has advanced significantly in domains like smart homes and fitness applications, including wearable sensors [21], its use in emergencies is still relatively limited and inconsistent. Emergencies present distinct challenges for HBC systems. These ongoing challenges make it clear that emergency systems must aim for high accuracy, respond in real time, tolerate noise, respect user privacy, and adapt easily to different environments and people. This study builds a strong and purposeful base for future research by closely examining what earlier research missed or struggled with. The selected studies mainly explore how machine learning and deep learning models are being used for HBC, especially in emergency settings that deal with diverse and multimodal data inputs [22]. The review is based on selected peer-reviewed papers from respected journals and conferences. These works cover different types of emergencies, sensor technologies and analytical techniques. Continued advancements and improvements in computing-related resources, access to large datasets [10] and the development of advanced intelligent

architectures like CNNs, RNNs [2] and attention-based hybrids have effectively and greatly accelerated progress in this domain. Some of the remarkable strengths of these models are that they can now extract detailed spatiotemporal patterns from multiple data sources [6,8].

As a result, they can recognise subtle behaviours even in unpredictable, real-time, or noisy conditions. Even though the number of research studies and practical applications is steadily increasing, several critical points still remain unresolved. One major concern is that many algorithms are still tested mainly on simulated datasets, which usually fall short of reflecting the true complexity and unpredictability of real-life scenarios. For example, which types of emergencies are most often studied in HBC research? What sensor combinations and data types are typically used? Which learning models demonstrate the greatest effectiveness? What limitations still hinder practical deployment? A significant contribution in this area is the introduction of the KFall dataset, which includes synchronised sensor and video data to support more accurate labelling and evaluation [10]. This review organises and examines existing studies based on specific research questions. Through this structured approach, it presents a broad view of both the technological developments and the methodological patterns found in emergency-focused HBC research. The key research questions driving this analysis are outlined below:

- RQ1: What types of emergencies are being addressed using human behaviour classification?
- RQ2: What multimodal datasets are commonly used?
- RQ3: Which sensors are commonly used?
- RQ4: Which ML/DL algorithms are most effective for HBC in emergencies?
- RQ5: What are the main limitations and gaps in current research?

These questions aim to uncover both the breadth and depth of the field, including applications such as fall detection for elderly individuals, evacuation monitoring in public buildings, violence or assault detection in surveillance footage and the prediction of large-scale environmental disasters like wildfires.

2 Background

Understanding human behaviour during emergencies has long intrigued researchers across disciplines such as psychology, biology and cognitive science [23]. Efforts have been made to classify behavioural patterns, particularly walking behaviours, by drawing on conceptual frameworks like rational thinking, habitual and impulsive reactions [24]. To build a more accurate and practical taxonomy, walking behaviour has also been interpreted through parallels with animal behaviours and further examined under both normal and high-stress conditions, such as those found in disaster scenarios [25]. Understanding how people make decisions when facing risk and uncertainty has long been a central challenge in behavioural science, psychology and economics [26]. Despite the structured nature of many experimental tasks, human choices often deviate from rational models. This unpredictability highlights the complexity of human behaviour across different disciplines [27]. HAR has gained much attraction in various smart home environments, especially to continuously monitor human behaviours in ambient assisted living to provide elderly care and rehabilitation [28]. In recent years, there has been a growing trend in the medical domain to explore methods for predicting human behaviour, particularly in the context of patient behaviour analysis [29]. Simulation of human behaviour has emerged as a critical component across various applications, especially in healthcare and social behaviour research. In addition, achieving accurate predictions is equally important to identify and understand the contributing factors behind human behaviour [30]. HAR in videos has long stood as an active area of research in computer vision and pattern recognition; steps for human activity recognition are represented in Fig. 2 from [31].

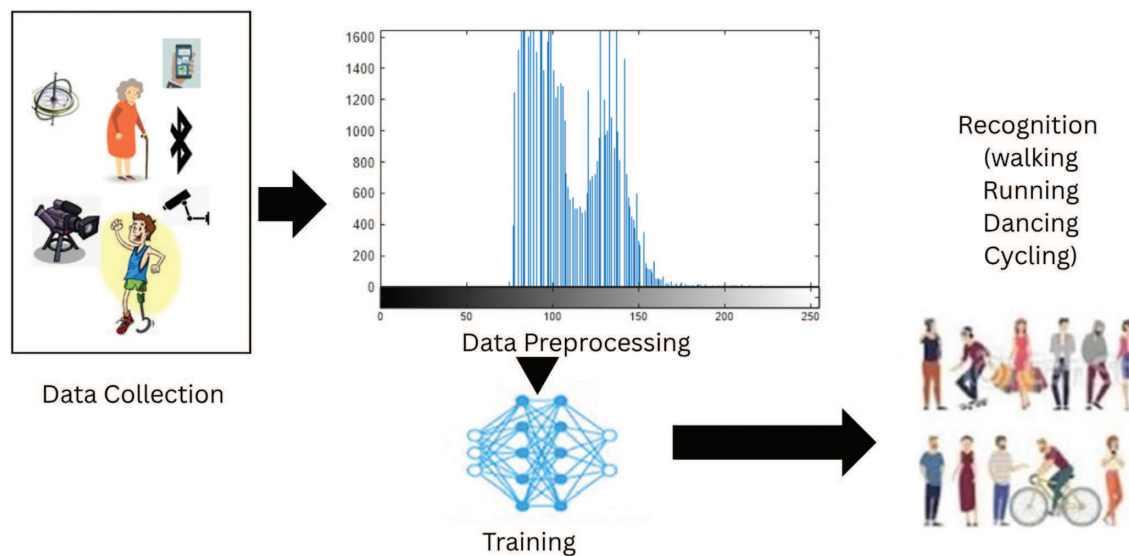


Figure 2: Steps for human action recognition process as described in [31]

Initially, the challenge was understanding how to detect and identify people, their behaviour and suspicious activities [32]. Over time, researchers discovered that spatial and temporal information played a crucial role in accurately recognising different human actions in complex scenes [33]. However, despite these advancements, precise recognition in real-world videos remained difficult. Factors such as motion style, occlusion and background clutter often hinder the correct identification of human actions under uncontrolled or crowded conditions [34]. A comprehensive and challenging benchmark shall be able to promote the research on human behaviour understanding, including action recognition, pose estimation, re-identification and attribute recognition [35]. Machine learning (ML) algorithms have emerged as a powerful tool for managing and interpreting Emergency situations, whether natural or human-made disasters [36]. Over the years, ML techniques have been increasingly applied in emergency management systems to support first responders and decision-makers, enhancing the overall capabilities in disaster prevention, preparedness, response and recovery [37]. Emergency management and response are critical aspects of ensuring public safety and security. Emergencies can take many forms, including natural disasters such as hurricanes, earthquakes and wildfires, as well as human-caused emergencies like terrorist attacks, industrial accidents [38] and pandemics [39]. Effective emergency response efforts during an emergency or natural disaster, as in Fig. 3, play a vital role in mitigating the impact of such events, helping to save lives and minimise property damage [40]. In recent years, there has been a surge in research focused on utilising social media for disaster response. This includes platforms like Facebook and “X” when used for communication during emergencies [41]. Many of these studies explore automated machine learning approaches to identify disaster-related posts [42], which play a crucial role in facilitating coordination and timely response. Besides physical sensors and other technical sources, individuals using smart mobile devices, often referred to as human sensors, generate vast amounts of multimodal data during crises, including text, audio, video and images. These datasets are typically categorised as multimodal, reflecting the diverse formats in which critical information is shared during emergencies [43]. The main challenges faced by emergency responders is effective extraction, analysis and interpretation of this multimodal data within a limited time frame for timely and informed decision-making.

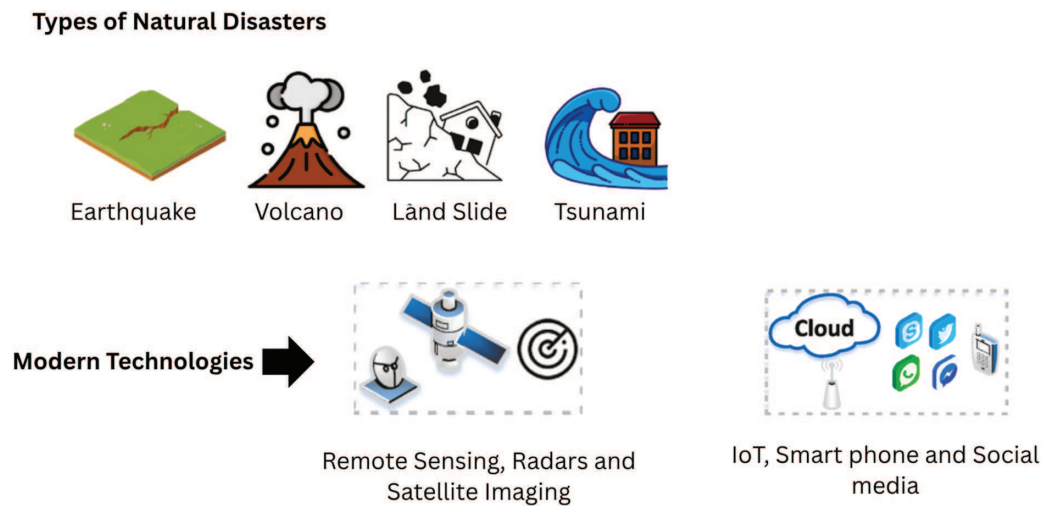


Figure 3: Types of Natural Disasters and the mitigating technologies as described in [40]

One of the key challenges in disasters is combining the excess of available information, ranging from social media data to satellite imagery and turning it into concrete and actionable insight [44]. This requires multi-modal data on disaster impact, location-based risk and spatial conditions [45], for disaster response. Although multimodal data fusion for disaster response has been applied to social media data, a research gap remains in incorporating other sources, such as satellite imagery or statistical data, to better capture the spatial context and exposure. During the occurrence of natural disasters, people heavily use social media for communication by posting multimedia information in the form of texts and images. In such critical situations, it becomes imperative to use all modalities of information sources to better capture vital knowledge related to the crisis [46]. Ignoring either modality (text or image) can lead to a partial understanding of the content.

In the year 2020, the COVID-19 pandemic drastically disrupted both private and public life [47], forcing many sectors around the world to shift to online modes of operation with little to no preparation time. The study of human behaviour, whether in daily life [48] or under high-stress conditions, shows how complex it truly is when viewed across different disciplines.

Over the years, progress has been made in areas like assisted living, healthcare and predictive behaviour systems, which have improved both the reliability and interpretability of results [49]. Fundamental aspects to be considered in the design of such systems are shown in Fig. 4. Yet, challenges are still there, especially in uncontrolled or crowded environments, where achieving accuracy becomes much more difficult. Even with the support of benchmarks and multimodal approaches, the success of disaster management still depends a lot on quick decision-making and proper preparedness. The rapid digital shift during crises like the COVID-19 pandemic also reminds us of the growing need for adaptive and resilient systems that can truly support emergency response.

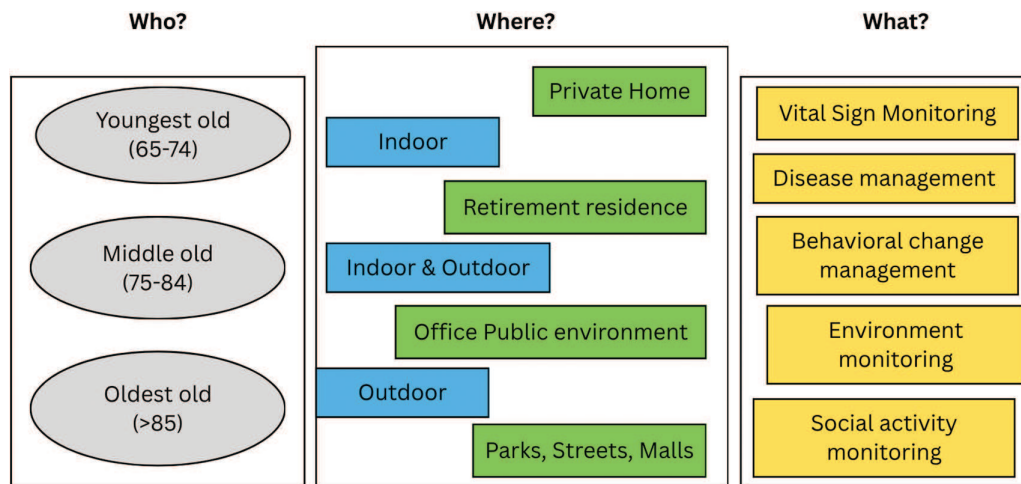


Figure 4: Fundamental aspects to be considered in the design and development of an AAL system: possible users (who?), environments (where?) and functionalities (what?) as described in [49]

3 Related Work

As a result of the new technological advancements and emergencies becoming more complex, there has been a noticeable rise in SLRs and meta-analyses exploring how human behaviour can be modelled and managed through AI systems. These recent studies have laid a strong foundation by discussing methods, approaches and highlighting the research gaps, like [50]. This current review shifts its focus towards classifying human behaviour during emergencies, especially by using machine learning (ML) and diverse data types. Comparing some of the most relevant recent studies to help place this work in the larger research picture and understand where it stands. One of the most comprehensive studies [51] presented a literature review focused on human behaviour during disaster evacuation processes. Their analysis synthesised 177 studies from 1954–2022 and emphasised the necessity of understanding individual and group behaviour for successful evacuation planning. The review highlighted several behavioural modelling techniques, including route choice behaviour, decision-making models, virtual reality simulations and agent-based approaches. Especially, the study pointed out the lack of focus on transportation evacuations, suggesting a gap in representing real-world urban scenarios. The authors also identified the key role of psychological, demographic and social characteristics in determining evacuee behaviour, aligning with the motivations behind HBC in our own study. The authors in [52] reviewed 134 papers from 2013–2023 and their work outlined challenges associated with current agent-based modelling (ABM) approaches, including computational limitations, scarcity of real-time behavioural data and the limited complexity of decision-making architectures. Their review highlights the importance of simulating adaptive and autonomous human-like behaviour in emergencies, which is a challenge directly addressed through ML-based HBC models and multimodal fusion techniques [53].

A broader perspective on decision-making support in emergency contexts is provided in [54], along with the use of decision support systems (DSS) in search and rescue (SAR) operations. Their study evaluated a wide range of AI-driven tools, including geospatial information systems, optimisation models and intelligent data fusion platforms used in SAR planning and response. While their work does not focus directly on behaviour classification, it reinforces the critical role of real-time, context-aware decision-making tools, of which HBC systems are a natural complement. A unique contribution from this review was the identification of knowledge transfer possibilities across domains such as environmental monitoring and maritime safety

domains, where behaviour classification has emerging relevance. Like [55], localisation is provided as an essential tool to ensure readiness, response, and coordination between first responders and affected individuals. They also worked on emerging sixth-generation (6G) wireless technologies such as integrated sensing and localisation. Their reviewed technologies can play an effective role in device localisation and are presented to serve as a base for others to further investigate and conduct research in this domain.

Reference [56] conducted an SLR on driver behaviour classification (DBC), an adjacent domain that similarly seeks to model and predict human actions in real-time and high-risk environments. Their analysis highlighted the types of behaviours classified (e.g., aggressive, distracted, abnormal) and categorised the use of ML/DL algorithms such as SVMs, CNNs and LSTMs across datasets like SHRP2 and NGSIM. Although the context is different in vehicular safety and emergency responses, the challenges in feature extraction, multimodal fusion and real-world deployment are very similar. This provides a conceptual bridge for applying DBC techniques to broader emergency HBC models.

Another study [57] focused on big data analytics (BDA) in humanitarian and disaster operations. Although this study was not centred purely on HBC, it strongly highlights the importance of large-scale multimodal data in managing crises. A critical insight from this review is the identification of persistent gaps in preventive modelling and early-warning systems, areas where predictive HBC systems using multimodal sensing could make substantial contributions. Together, these related reviews demonstrate the depth and interdisciplinarity of the field, covering evacuation modelling, pedestrian dynamics, SAR coordination, driver behaviour and humanitarian logistics.

However, none of these works provide a comprehensive and focused synthesis of HBC specifically in emergency situations using multimodal data and machine learning methods. Our review emphasises the live classification and real-time understanding of human actions, especially in high-risk, time-sensitive environments. It also bridges methodologies from adjacent fields and connects them through the lens of multimodal fusion and ML-enhanced behavioural modelling. Reference [58] provided a detailed overview of the latest advancements in real-time fall prediction using wearable sensors. A comprehensive review was carried out on various studies that employed different machine learning techniques and sensor modalities to predict falls in real time. It describes the problems and limitations associated with wearable sensor-based fall prediction. It identifies the possible future research directions in this field and provides a comprehensive narrative review of the recent research on fall risk assessment using wearable sensors and gait analysis. The importance of Radio frequency (RF) spectrum sensing is key for the purpose of precise object posture detection and its classification. Reference [59] aims for a focused review of context-aware RF-based sensing, emphasising its principles, advancements and issues. Reference [60] highlighted the importance of abnormal behaviour detection (ABD) in activities of daily life (ADL). The author compared and contrasted the formation of the ABD system in ADL from input data types (sensor-based input and vision-based input) to modelling techniques (conventional and deep learning approaches). Review [61], comprising 424 studies, investigates the integration of machine learning (ML), deep learning (DL), computer vision, IoT-enabled predictive analytics and AI-powered robotics in shifting emergency response mechanisms. It also investigates the integration of machine learning (ML), deep learning (DL), computer vision, IoT-enabled predictive analytics and AI-powered robotics in shifting emergency response mechanisms. It comprehensively examines AI applications in disaster management, real-time incident detection, healthcare emergency response, industrial hazard prevention, cybersecurity frameworks and intelligent traffic control, which provides a comprehensive assessment of advancements and problems in AI adoption.

3.1 Contribution

- This study classifies the various types of emergencies, including falls, evacuation scenarios, violent incidents, wildfires and medical crises.
- It examines the application of multimodal datasets, emphasising the frequent use of publicly accessed datasets like SisFall [62] and UCI-HAR [63], along with custom-built and synthetic data sources for emergency-related studies.
- This study analyses and records the range of sensors employed in the selected studies. These include inertial measurement units (IMUs), thermal and RGB cameras, environmental detectors and different wearable systems equipped with multiple sensors.
- Various ML and DL approaches were reviewed and compared to assess how good they perform in behaviour classification tasks during emergency situations.
- Some of the major research challenges and gaps, which include the lack of real-world generalizability, inconsistent dataset standards, difficulties in integrating multimodal inputs and limited focus on vulnerable or at-risk populations.

3.2 Review Methodology

This review follows the PRISMA framework, which is recognised as the most reliable approach to conduct a systematic review, as illustrated in Fig. 5. The PRISMA checklist is provided as Supplementary Material attached to this paper. A structured approach was maintained, examining peer-reviewed studies published between 2020 and 2025, and stating five key research questions (RQ1–RQ5). These questions were carefully formulated to ensure alignment with the main theme and to refine the specific focus of the study.



Figure 5: SLR review protocol

3.3 Search Strategy

The search strategy involved querying multiple digital databases, including IEEE Xplore, ScienceDirect, SpringerLink, MDPI, and Elsevier, using a predefined set of keywords accompanied by Boolean operators and wildcard characters for the sake of expanding search scope. Main search terms included combinations of:

- “Human behaviour classification” or “activity recognition”
- “Emergency” or “disaster” or “evacuation” or “fall detection”
- “Multimodal data” or “sensor fusion”
- “Machine learning” or “deep learning”

The time range was restricted to 2020–2025. Only English-language, peer-reviewed journals and conference papers were included.

3.4 Inclusion and Exclusion Criteria

In order to ensure the relevance and quality. We applied following criteria.

Inclusion Criteria:

- Studies published between 2020 and 2025.
- Focus on human behaviour recognition/classification in emergency contexts.
- Use of machine learning or deep learning models.
- Utilisation of multimodal or multi-sensor data (vision, inertial, environmental, etc.).
- Peer-reviewed journal or conference publications.

Exclusion Criteria:

- Papers outside the specified date range.
- Studies focusing solely on non-emergency activities.
- Articles lacking ML/DL or sensor-based approaches.
- Non-peer-reviewed work (e.g., preprints, editorials, theses).
- Duplicate or redundant studies.

3.5 Quality Assessment Criteria

Each included study was given a quality score, assigning binary number (0 or 1) across the following dimensions:

- Relevance: Is the study focused on HBC in emergencies?
- Technical Rigour: Does the study present a valid and replicable ML/DL methodology?
- Data Modality: Does the study use more than one modality or sensor type?
- Results and Evaluation: Are the model performance metrics clearly reported?
- Contribution: Does the study present a novel architecture, dataset, or insight?

Fig. 6 presents a thorough overview of our screening and assessment method for the statistical analysis of our literature.

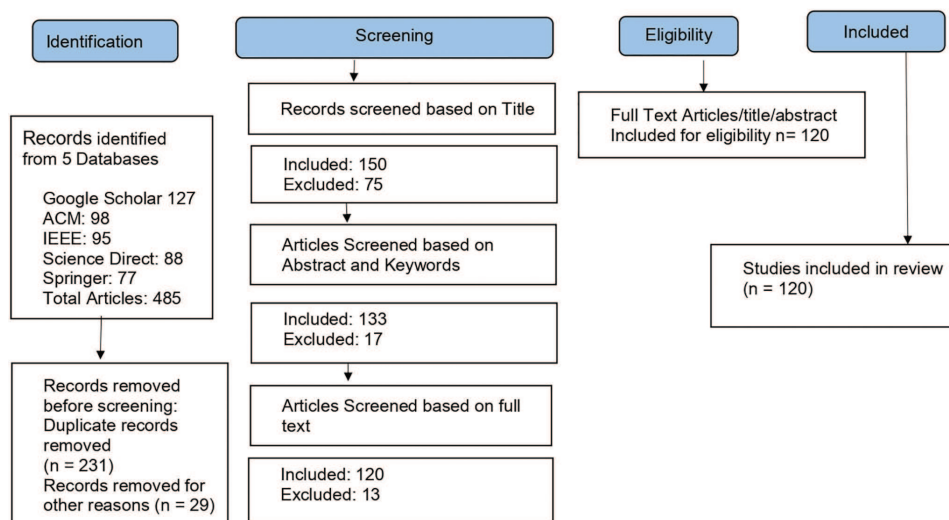


Figure 6: Flow diagram of screening

3.6 Quantitative Analysis

A total of 120 papers were selected as a result of a detailed review, subsequently applying the inclusion, exclusion and quality criteria. Quantitative analysis was conducted to identify:

- Publication trends by year (2020–2025)
- Frequency of emergency types addressed (e.g., fall detection, evacuation, fire, violence)
- Sensor distribution (e.g., IMU, camera, thermal, environment)
- Modalities used (vision-only, wearable-only, multimodal fusion)
- ML/DL algorithm usage (e.g., CNN, LSTM, hybrid models)
- Dataset types (public, custom, simulated)

This structured approach ensured the reliability, reproducibility and thematic alignment of the review with the defined research objectives.

4 Outcomes

RQ1: What types of emergencies are being addressed using human behaviour classification?

The above-mentioned question highlights the wide spectrum of emergencies studied under human behaviour classification. Starting from personal health crises to societal scale disasters as represented in Table 1. The outcomes state that broader integration of multimodal data, real-world deployment and context-aware generalisation remain key directions for future research. Emphasising the importance of detecting fall-related events in vulnerable populations such as the elderly, disabled, or patients in assisted living. It is demonstrated that social media, environmental data and multimodal fusion are vital for rapid situational awareness. Extending human behaviour classification to include help-seeking behaviours, evacuation monitoring and even wildfire prediction. The literature addressed physical hazards in workplace environments. The use of wearable sensors and motion analysis reflects their practical use in high-risk industries. Both physical cues (e.g., “hands up” poses, frantic running) and digital signals (e.g., misinformation on social media) as indicators of emergencies. However, privacy concerns, scalability in crowded scenarios and real-time deployment challenges remain open issues.

Table 1: Research gap table for RQ1: What types of emergencies are being addressed using human behaviour classification?

Falls and Elderly Care Emergencies			
Sr. No.	References	Emergencies addressed	Research gaps
1	[64]	Deaths during Pandemic	Limited to deaths of left alone people
2	[65]	Lonely deaths, health crises in SPHs	Limited to SPHs; ignores large-scale emergencies
3	[66]	Disabilities affect the individuals physical and mental health	Only health conditions are focused in activities of daily life
4	[67]	Elderly falls	No other emergency types
5	[68]	Elderly abnormal behaviours	Indoor-limited
6	[69]	Elderly falls	Elderly-focused
7	[70]	Indoor/healthcare falls	No public/industrial context
8	[71]	Falls in vulnerable people	Doesn't address complex disaster events

(Continued)

Table 1 (continued)

9	[72]	Falls, injuries	Healthcare limited
10	[73]	Elderly falls	Elderly-only focus
11	[74]	Falls in various populations	Falls only; no other emergencies
12	[63]	Falls in healthcare	Healthcare-specific
13	[62]	Elderly fall detection	Elderly-limited
14	[75]	Thermal detection of falls	Healthcare/privacy-focused
15	[76]	Abnormal behaviour in assisted living	Indoor-specific
16	[77]	Occupational falls	Workplace-only scope
Natural Disasters and Crisis Management			
17	[37]	Extreme weather events	Integrating big data from different sources (e.g., weather radar systems and rainfall and water river gauges)
18	[78]	Large-scale disaster	Limited to only three countries
19	[79]	Disaster assessment and management	Data uncertainty on social media
20	[80]	Natural disasters	Misses on-ground actions, limited accuracy
21	[81]	Disaster coordination	Focuses on coordination, not classification
Natural Disasters and Crisis Management			
22	[82]	Crowd panic, destruction	Depends on social media; lacks physical context
23	[83]	Disasters: floods, fires, etc.	Broad but not behaviour-focused
24	[84]	Chemical spills	Evacuation focus, not behaviour
25	[85]	Disaster management	Data-focused; lacks behaviour classification
26	[86]	Disaster emergencies	Post-disaster only; no real-time behaviour
27	[87]	Wildfire behaviour impact	Environment-focused
28	[14]	Evacuation during disasters	Evacuation only
Industrial/Occupational Emergencies			
29	[88]	Chemical spills, explosions, nuclear accidents	Technological disasters only
30	[89]	Factory emergencies	Industrial-only scope
31	[90]	Fall accidents in workers at construction sites	limited to worker-related fall accidents in general building construction
32	[91]	Psychological stress	Not physical/environmental emergencies

(Continued)

Table 1 (continued)

Public Safety, Crowd and Social behaviour			
33	[92]	Disaster evacuations	No physical behaviour detection
34	[93]	Misinformation in crises	Not physical emergency detection
35	[94]	Panic behaviour within a human crowd	Lower accuracy when tested on the festival videos
36	[95]	Panic in crowd evacuations	Narrow emergency scope
37	[96]	Disasters in public spaces	No real-world chaotic validation; narrow focus
38	[97]	Multiple critical emergencies	Only classifies calls; not physical detection
39	[98]	Assault/crime detection	No natural disaster detection
40	[99]	Falls, abrupt movements	Sensor simulation only

RQ2: What multimodal datasets are commonly used?

For the demonstration, that progress in human behaviour classification for emergencies is shaped by the diversity and availability of datasets. The discussed above Datasets enable crisis monitoring, fall detection, evacuation analysis and disaster forecasting. Still, there exist some issues, including noisy or incomplete annotations, limited real-world generalisation, imbalance across event types and ethical concerns related to privacy and surveillance are also discussed. Efforts are concentrated on fall detection, activity recognition and stress monitoring. Public benchmarks such as SisFall and KFall played a central role, while custom datasets addressed workplace, smart home and clinical environments. CrisisMMD and Hurricane Harvey collections have been widely applied for crisis informatics. They capture help-seeking behaviours, misinformation and rumour propagation, providing rapid situational awareness. It has been shown that emergency call recordings and speech-to-text conversions serve as valuable multimodal resources. These datasets provide unique real-time communication cues, with challenges in noisy environments, caller variability and limited availability due to privacy constraints. Lastly, by fusing imagery, climate and geospatial data, these datasets enable large-scale forecasting and evacuation planning. However, they lack fine-grained human-level behavioural details, limiting their integration with micro-scale human activity datasets as shown in Table 2. The fusion of multimodal data enables richer context awareness, reduces ambiguity and enhances model robustness under complex conditions, while a single source data stream alone might fail. But for, the integration of multimodal sources may require overcoming challenges like synchronisation across modalities, differing sampling rates, data imbalance and computational overhead.

Table 2: Research gap table for RQ2: What multimodal datasets are commonly used?

Sr. No.	References	Dataset	Research gaps
Sensor Based and Wearable Multimodal Datasets			
1	[65]	Custom sound recordings (audio) with labelled activity states (fall, gas leak, etc.)	Limited to single household environments; does not address diverse, large-scale emergency datasets.

(Continued)

Table 2 (continued)

Sr. No.	References	Dataset	Research gaps
2	[96]	Smartphone sensor data (accelerometer, gyroscope) capturing various activities	Lacks real-world disaster data; only simulates disaster conditions in controlled settings.
3	[77]	Multiple wearable sensor datasets (biomechanical motion data from accelerometers and gyroscopes)	Limited to wearable data; lacks integration of external environmental sensors or multimodal data fusion.
4	[89]	Custom dataset (inertial and proximity sensor data from factory settings)	Limited to industrial environments; does not address broader emergency detection or public safety contexts.
5	[67]	Custom skeleton dataset (RGB-D depth images and 2D pose estimations) for fall detection	Limited to indoor and healthcare settings; does not cover broader types of emergencies (e.g., natural disasters).
6	[68]	IoT-based ADL dataset (sensor data on movement, temperature, room occupancy)	Indoor setting focus; lacks multimodal external data (e.g., environmental or audio sensors).
7	[69]	SisFall dataset (accelerometer + gyroscope data for fall scenarios)	Limited to fall detection; does not incorporate other types of emergency scenarios.
8	[70]	Custom dataset (wearable sensors + vision/RF for fall and activity classification)	Limited to healthcare environments; does not address other emergency scenarios like public safety or industrial emergencies.
9	[100]	RF sensing dataset (captures fall and movement events)	RF-based data is limited to indoor environments; lacks broader multimodal sensor integration.
10	[84]	Chemical accident datasets (incident records, demographic data, environmental data)	Limited to chemical accidents; does not focus on real-time behavioural classification or broader emergency types.
11	[91]	Multimodal office dataset (mouse/keyboard data, heart rate variability, stress reports)	Focus on stress detection; does not address physical emergencies or large-scale disaster scenarios.
12	[73]	PIR sensors dataset (motion and fall events from 20 participants)	Limited to fall detection; lacks other emergency types or external data sources.
13	[76]	RGB video datasets (MSRDailyActivity3D, PRECIS HAR, UCF11) for activity classification	Limited to daily living activities; does not include emergency or crisis scenarios.
14	[98]	Video surveillance data + smartphone sensors (location, time) for detecting postures (e.g., “hands up”)	Limited to personal safety and pose recognition; does not address broader public emergency behaviour.

(Continued)

Table 2 (continued)

Sr. No.	References	Dataset	Research gaps
15	[74]	Wearable sensor data (accelerometer, gyroscope, pressure sensors) for fall detection	Limited to fall detection; lacks real-time response behaviour in broader disaster contexts.
16	[63]	Human activity recognition datasets (UCI-HAR, KU-HAR, WISDM, HMDB51) combining accelerometer, gyroscope and video data	Limited to human activity recognition; does not cover emergency situations like disasters.
17	[62]	KFall and SisFall datasets (wearable accelerometer and gyroscope data) for fall detection	Focused on elderly fall detection; doesn't address other emergency types.
18	[99]	REALDISP and REALWORLD IMU datasets for simulating human activity recognition	Limited to simulation data; does not use real-world multimodal datasets.
19	[75]	Infrared array sensor data capturing thermal signatures during activities (fall detection)	Limited to fall detection; does not address a wide range of emergency scenarios.
20	[95]	Multimodal biometric + spatiotemporal dataset (heart rate + location data) for panic detection	Limited to biometric and location data; lacks inclusion of other environmental sensors or physical behaviours.
21	[72]	Video datasets (surveillance footage for activity recognition)	Focus on healthcare settings; lacks integration with environmental or social context data.
Social Media and Crowdsourced Disaster Datasets			
22	[101]	CrisisMMD dataset	Heavily focused on textual content analysis.
23	[80]	CrisisMMD dataset (social media images + tweet text + annotations) during disasters	Focus on post-event social media data; does not capture real-time sensor-based multimodal data.
24	[102]	Sina-Weibo ("X" like microblogging services in China)	Emperically defined spatial scale
25	[81]	Social media dataset (text tweets + spatial metadata) during Hurricane Harvey	Lacks traditional sensor data; focuses more on social media than real-time emergency detection.
26	[82]	Custom multimodal dataset (images + sentiment/activity labels from social media posts)	Dependency on user-generated data; lacks integration of sensor-based or real-time emergency data.
27	[93]	Large-scale social media dataset (text + temporal and social network metadata)	Focus on social media data; no sensor-based emergency data or real-time monitoring.

(Continued)

Table 2 (continued)

Sr. No.	References	Dataset	Research gaps
28	[83]	Survey of multimodal datasets used across disaster management literature (satellite imagery, sensor networks, weather data)	Broad review; lacks a focus on specific behaviour classification or sensor data fusion.
29	[85]	Multimodal disaster data (social media, images, audio, video) for situational awareness	Focus on data presentation; lacks integration of real-time emergency classification data.
30	[103]	Public multimodal crisis datasets	Existing datasets like CrisisMMD are small and limit model generalization. Limited to post-disaster aid; does not focus on real-time behaviour
31	[86]	Crowdsourced social media data (text + images) during natural disasters	recognition or physical emergency situations.
32	[92]	Multimodal tweet dataset (text + images from disaster-related tweets)	Limited to social media data; lacks real-time sensing data or physical activity monitoring.
33	[14]	HBDset dataset (images with bounding boxes for human behaviour categories in evacuation scenarios)	Limited to evacuation behaviour; lacks broader emergency classifications.
Audio, Speech and Voice Datasets			
34	[104]	Custom dataset for medical speech utterances	Limited to speech classification.
Remote Sensing, Satellite and Environmental Datasets			
35	[97]	Voice-to-text emergency call dataset (converted speech data from emergency calls)	Focus on textual data; lacks use of physical sensors or real-time event data.
36	[87]	Satellite remote sensing imagery + environmental data (wind, land cover) for wildfire prediction	Focus on environmental data; lacks human behavioural classification for emergency detection.

RQ3: Which sensors are commonly used?

The human behaviour classification in emergencies relies on a highly diverse spectrum of sensing modalities, ranging from traditional to fully digital, as shown in Table 3. This diversity reflects both the complexity of emergency contexts and the complementary strengths of different sensor types. Microphones and speech-to-text pipelines are advantageous for unobtrusive monitoring in households or dispatch systems, but remain sensitive to environmental noise and caller variability. Accelerometers, gyroscopes, magnetometers and stretch sensors dominate fall detection and activity recognition. But issues such as body placement, user compliance and energy efficiency remain open. Vision and Depth-based Sensors discussed above provide rich spatial-temporal information but face scalability, occlusion and privacy-related concerns, particularly in public monitoring scenarios. Radio Frequency, Environmental and Remote Sensing Sensors

extend emergency monitoring to larger environmental and infrastructural scales, but they often lack fine-grained individual-level details helpful for behaviour classification. Social Media/Digital Sensing are treated as “virtual sensors” where human posts, images and geolocation data act as dynamic signals. This paradigm supports real-time situational awareness with a high risk of incomplete data and misinformation. Ambient IoT and Contextual Sensors. While effective for localised monitoring, they require dense deployment and may lack portability across diverse environments.

Table 3: Research gap table for RQ3: Which sensors are commonly used?

Sr. No.	References	Sensors	Research gaps
Acoustic and Voice Based Sensors			
1	[65]	Microphone sensors for acoustic event detection (e.g., coughing, falling)	Limited to passive acoustic sensing; lacks more complex multimodal sensor systems.
2	[97]	Voice input data (speech-to-text conversion) for emergency call classification	Limited to voice-based data; lacks real-time sensor-based emergency event detection.
Smartphone and Wearable Inertial Sensors			
3	[96]	Smartphone sensors (accelerometer, gyroscope)	Limited to smartphone-based sensors; does not incorporate more complex or external sensors like vision or environmental sensors.
4	[77]	Wearable Stretch Sensors (WSS), Soft Robotic Stretch (SRS) sensors for motion and posture monitoring	Limited to wearable and biomechanical sensors; lacks integration with environmental or visual data.
5	[105]	Accelerometer and gyroscope	Lack of angular and displacement data
6	[89]	Proximity sensors, IMU-based motion sensors	Limited to industrial environments; does not explore other sensor modalities like cameras or environmental sensors for wider applications.
7	[106]	IMU-based sensors	Not good for urgent systems due to late response.
8	[69]	Wearable IMU sensors (accelerometers, gyroscopes)	Limited to fall detection; lacks broader emergency event classification or multimodal sensor fusion.
9	[70]	Wearable sensors (accelerometers, gyroscopes), non-contact sensors (cameras, RF)	Limited to healthcare environments; does not address larger-scale emergencies like natural disasters.
10	[95]	Wearable biometric sensors (heart rate), spatial tracking devices (GPS)	Limited to biometric and location sensors; lacks multimodal sensor fusion for broader emergency contexts.

(Continued)

Table 3 (continued)

Sr. No.	References	Sensors	Research gaps
11	[107]	Textile-based wearable sensor monitored each participant's HRV	Limited for labour.
12	[91]	Biometric sensors (HRV, GSR), mouse/keyboard activity tracking	Limited to office environments; lacks coverage of physical emergencies and environmental hazards.
13	[73]	Passive infrared sensors (PIR), wearable accelerometers	Limited to fall scenarios in elderly care; lacks application to broader public emergencies.
14	[74]	Accelerometer, gyroscope, pressure sensors in wearable devices	Focused on fall detection; lacks application to diverse emergency types.
15	[63]	Wearable sensors + video streams	Focused on healthcare activity detection; lacks broader emergency behaviour recognition.
16	[62]	Accelerometer and gyroscope data from wearable devices	Focused on elderly fall detection; lacks general emergency applications.
17	[99]	IMU sensor simulation datasets	Uses simulated IMU data; lacks real-world emergency scenario validation.
Vision and Depth Based Sensors			
18	[67]	RGB-D cameras (depth sensors) to capture human skeleton data	Limited to depth sensors; lacks integration with wearable sensors or environmental data.
19	[108]	Body displacement sensors	Large number of classes were not tested.
20	[72]	Surveillance cameras, medical IoT sensors	Focused on healthcare; lacks environmental or multimodal integration for general emergency classification.
21	[76]	RGB cameras, accelerometers	Focused on normal activity recognition; lacks emergency detection in public or industrial settings.
22	[98]	Pose recognition from video + GPS and time data from mobile devices	Focused on safety gestures; lacks environmental context and real-time multimodal sensor fusion.
23	[14]	Computer vision-based camera data (evacuation scenarios)	Limited to visual data; lacks other sensor modalities like acoustic or biometric sensing.

(Continued)

Table 3 (continued)

Sr. No.	References	Sensors	Research gaps
24	[75]	Infrared array sensors (thermal) for activity recognition	Focused on thermal data; lacks integration with other modalities or emergency scenarios.
Radio Frequency, Environmental and Remote Sensing Sensors			
25	[71]	Radio frequency (RF) sensing for fall detection	Limited to indoor environments; lacks integration with wearable or visual sensors for broader detection capabilities.
26	[109]	mmWave Radar	Data set collected from young volunteers only.
27	[83]	Satellite imagery, UAVs, sensor networks (temperature, seismic, humidity)	Broad sensor review; lacks focus on human behaviour classification or real-time sensor networks for emergencies.
28	[84]	Environmental sensors (gas sensors, temperature monitors)	Focused on chemical accident evacuation; lacks broader behaviour classification and real-time detection capabilities.
29	[87]	Satellite imagery, environmental sensors (wind, temperature)	Focused on wildfire prediction; lacks integration with human-centered sensors for behaviour classification.
Social Media/Digital Sensing			
30	[80]	No physical sensors; relies on social media data (images, text)	No real-time physical sensors; focuses on virtual data from social media, which may not provide accurate real-time behaviour recognition.
31	[110]	Visual feed	High computational complexity.
32	[81]	Social media data (geolocation and textual data from tweets)	Lack of physical sensor data; focuses on crowd-sourced data from social media, limiting real-time sensor integration.
33	[111]	Social media	Untrusted or misleading social media posts.
34	[82]	No physical sensors; uses social media images and sentiment labels	Relies solely on social media data; no direct sensor-based data or real-time physical emergency detection.
35	[92]	Text and image data from social media platforms	Limited to social media; does not incorporate physical sensor data or real-time detection.

(Continued)

Table 3 (continued)

Sr. No.	References	Sensors	Research gaps
36	[112]	Digital Sensing	Limited integration and diversity of sensors.
37	[68]	Ambient IoT sensors (motion detectors, temperature, occupancy sensors)	Limited to smart home environments; lacks multimodal sensor integration with real-time emergency data from other domains (e.g., disasters).

RQ4: Which ML/DL algorithms are most effective for HBC in emergencies?

Convolutional and Deep Neural Networks:

Reference [65] demonstrated the effectiveness of CNNs for emergency sound recognition. Fig. 7 uses spectrogram-based representations and data augmentation techniques to achieve strong performance in real-time classification [113]. Study [114] showed that combining VGG16 for images with a custom CNN, as shown in Fig. 8, significantly outperformed unimodal baselines when classifying disaster-related text in a multimodal architecture [80].

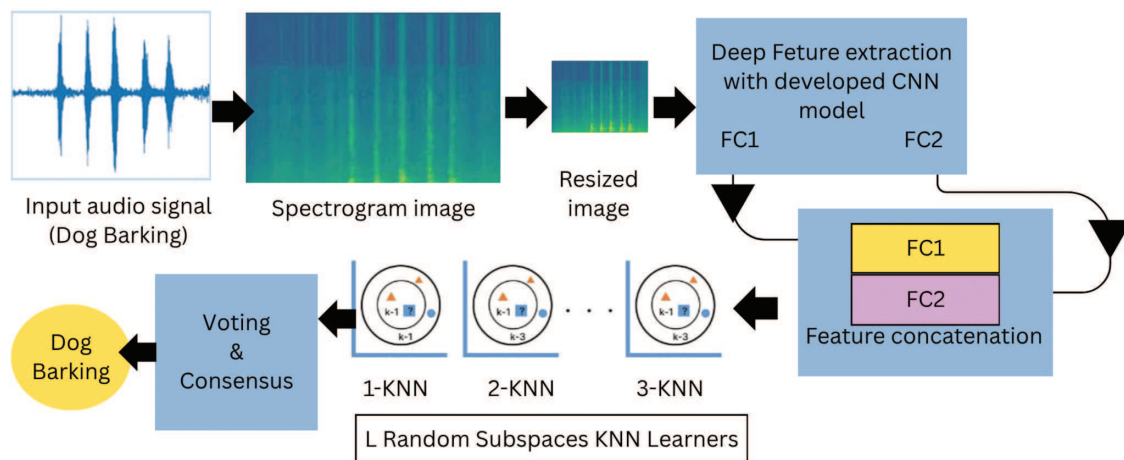


Figure 7: A Deep CNN model for environmental sound classification by [113]

The use of a k-nearest neighbour classifier for behaviour recognition and anomaly detection is shown in Fig. 9 [115]. In [68], the authors used an ADL dataset and achieved up to 83.87% accuracy in detecting anomalies in user behaviour that could constitute an emergency.

In Fig. 9, data collection and processing were conducted in Stage 1. In Stage 2, an optimised K Nearest Neighbour prediction model was constructed to make predictions of new sample data. Stage 3 is the quantitative analysis of the influencing factors of public support.

Reference [69] compared multiple ML algorithms, including kNN, Decision Tree, SVM, Random Forest and Gradient Boosting. Fig. 10 finds that Random Forest and Gradient Boosting achieved the highest sensitivity and specificity.

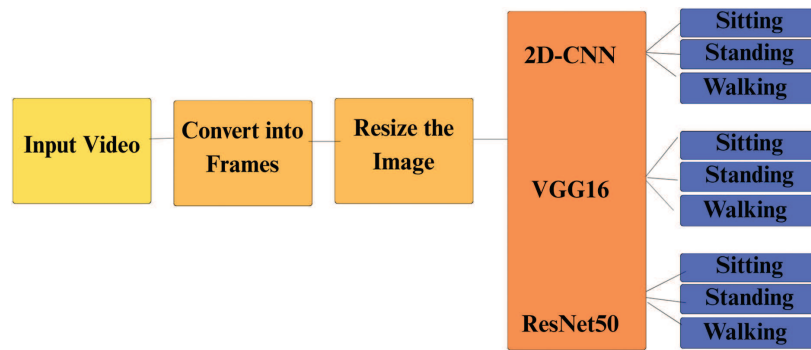


Figure 8: Block diagram of human behaviour classification system with training the 2D CNN model, VGG16 and ResNet50 by [114]

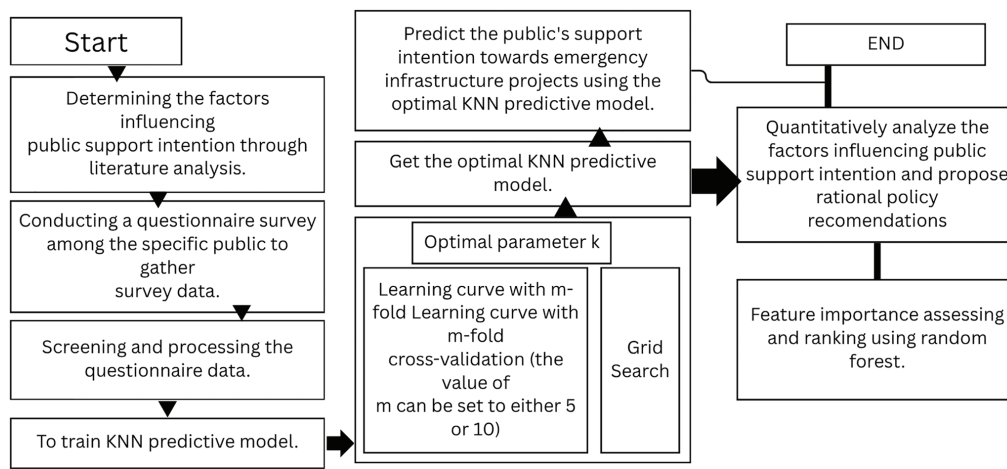


Figure 9: Division of research framework into a three-step process [115]

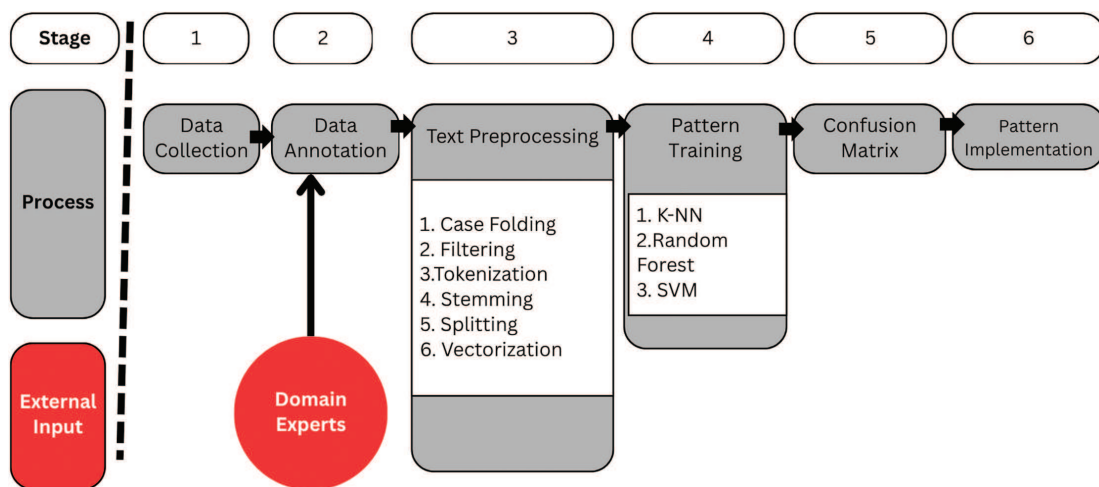


Figure 10: Stage-wise process division and comparison of algorithms by [116]

Chander et al. (2020) and Singh et al. (2020) presented a review highlighting pattern recognition and adaptive signal processing techniques for interpreting WSS sensor data in fall detection systems [77], as represented in Fig. 11.

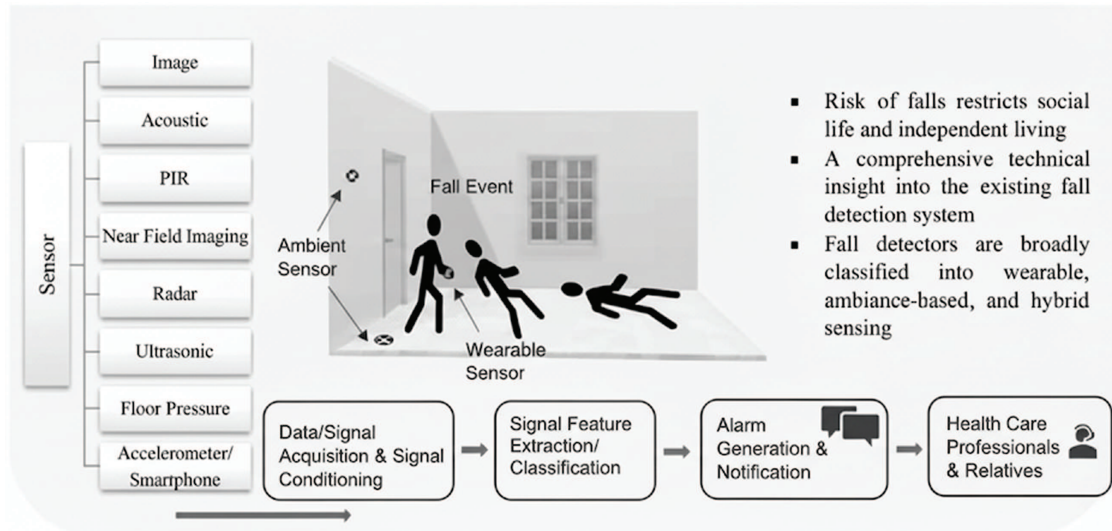


Figure 11: Fall Detectors classification and alarm generation by [117]

Linardos et al. (2022) highlighted CNNs, RNNs (LSTM), Transformers and ensemble methods as effective techniques for prediction, classification and early warning in disaster management Fig. 12, as discussed in the review by [83].

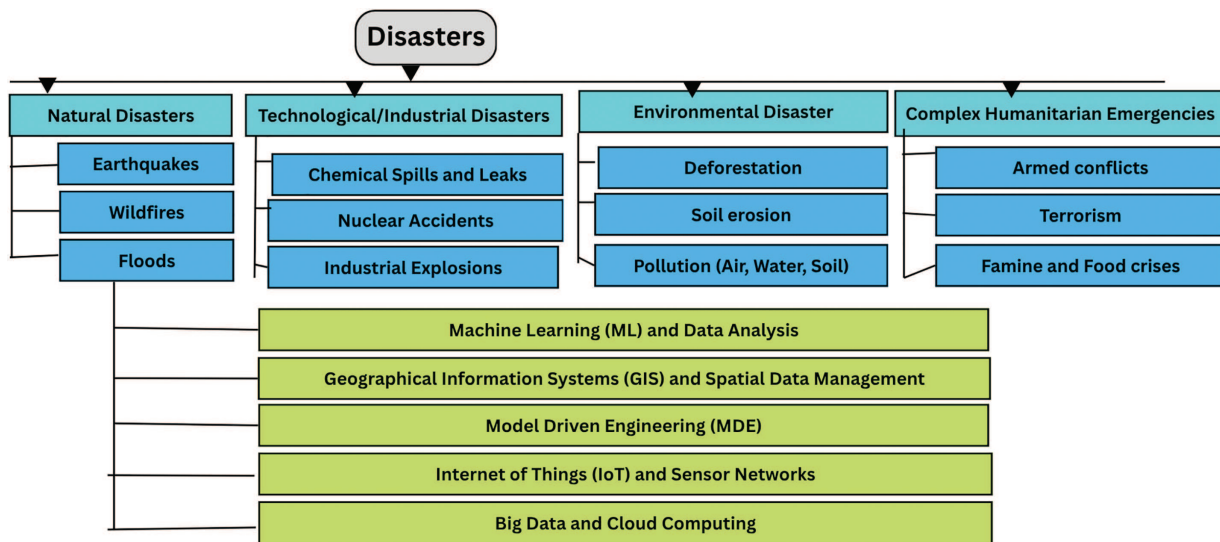


Figure 12: Review of disaster management system approaches by [118]

The research question in consideration shows that deep learning models dominate human behaviour classification in emergencies, as shown in Table 4, with CNNs, LSTMs and hybrid CNN-LSTM frameworks consistently outperforming traditional ML approaches. Transformer-based models and ensemble architectures are emerging as promising alternatives, particularly for multimodal text-image classification and

interpretability. Convolutional and Deep Neural Networks are highly effective for spatial and multimodal feature learning. Hybrids such as CNN-LSTM and CNN-SVM further enhance classification accuracy by utilising complementary strengths. Recurrent Models demonstrate clear advantages for sequential data, outperforming feedforward and CNN-only models in capturing temporal dynamics for falls, postures and evacuation monitoring. Classical ML Algorithms still hold value in domains requiring interpretability or constrained computation. However, they often underperform compared to DL models, except in structured or low-dimensional sensor datasets where Random Forest and AdaBoost achieve strong accuracy. Reinforcement Learning and Heuristic Approaches extend the field beyond recognition toward adaptive coordination, decision making and rumour detection.

Table 4: Research gap table for RQ4: Which ML/DL algorithms are most effective for HBC in emergencies?

Sr. No.	References	Algorithms and technique	Research gaps
Convolutional and deep neural networks			
1	[65]	CNNs	Limited to passive acoustic sensing; lacks more complex multimodal sensor systems.
2	[80]	VGG16 for images with a custom CNN	No real-time physical sensors; focuses on virtual data from social media, which may not provide accurate real-time behaviour recognition.
3	[82]	YOLO	Relies solely on social media data; no direct sensor-based data or real-time physical emergency detection.
4	[67]	BiLSTM and CNN	Limited to depth sensors; lacks integration with wearable sensors or environmental data.
5	[70]	CNNs and LSTM	Limited to healthcare environments; does not address larger-scale emergencies like natural disasters.
6	[71]	Deep neural networks	Limited to indoor environments; lacks integration with wearable or visual sensors for broader detection capabilities.
7	[86]	Advanced deep learning architectures	Post-disaster analysis only; lacks physical sensor data and real-time emergency detection capabilities.
8	[72]	Hybrid model integrating CNNs with SVMs	Focused on healthcare; lacks environmental or multimodal integration for general emergency classification.
9	[92]	Fine-tuned RoBERTa for text and Vision Transformer for images	Limited to social media; does not incorporate physical sensor data or real-time detection.

(Continued)

Table 4 (continued)

Sr. No.	References	Algorithms and technique	Research gaps
10	[119]	Transformer-based Pre-trained Language Models (PLMs)	Uncertain Social Media Data.
11	[76]	Hybrid CNN LSTM model	Focused on normal activity recognition; lacks emergency detection in public or industrial settings.
12	[87]	MA Net and ConvLSTM architectures	Focused on wildfire prediction; lacks integration with human-centered sensors for behaviour classification.
13	[74]	Compact CNN LSTM model	Focused on fall detection; lacks application to diverse emergency types.
14	[63]	HARCNN, a CNN based architecture	Focused on healthcare activity detection; lacks broader emergency behaviour recognition.
15	[14]	YOLO	Limited to visual data; lacks other sensor modalities like acoustic or biometric sensing.
16	[62]	Ensemble model integrating CNNs with channel attention and BiLSTMs with temporal attention.	Focused on elderly fall detection; lacks general emergency applications.
17	[99]	BiLSTM and CNN	Uses simulated IMU data; lacks real-world emergency scenario validation.
18	[120]	Recurrent and Feedforward neural network	Supports only english text.
Recurrent models			
19	[96]	LSTM	Limited to smartphone-based sensors; does not incorporate more complex or external sensors like vision or environmental sensors.
20	[84]	1D Convolutional Neural Network	Focused on chemical accident evacuation; lacks broader behaviour classification and real-time detection capabilities.
21	[89]	Proximity sensors, SVM classifiers	Limited to industrial environments; does not explore other sensor modalities like cameras or environmental sensors for wider applications.

(Continued)

Table 4 (continued)

Sr. No.	References	Algorithms and technique	Research gaps
22	[68]	K-NN	Limited to smart home environments; lacks multimodal sensor integration with real-time emergency data from other domains (e.g., disasters).
23	[69]	k NN, Decision Tree, SVM, Random Forest	Limited to fall detection; lacks broader emergency event classification or multimodal sensor fusion.
24	[116]	k-Nearest Neighbours, Random Forest, Support Vector Machine and AdaBoost	limited accessibility of localised tools and techniques.
25	[95]	SVM, random forest	Limited to biometric and location sensors; lacks multimodal sensor fusion for broader emergency contexts.
26	[91]	Gradient boosting	Limited to office environments; lacks coverage of physical emergencies and environmental hazards.
27	[73]	Random Forest, Decision tree and SVM	Limited to fall scenarios in elderly care; lacks application to broader public emergencies.
28	[98]	SUPervised ML Classifiers	Focused on safety gestures; lacks environmental context and real-time multimodal sensor fusion.
29	[75]	ILSTM, K-NN and SVM	Focused on thermal data; lacks integration with other modalities or emergency scenarios.
Reinforcement learning and heuristic/Rule based approaches			
30	[81]	ResQ	Lack of physical sensor data; focuses on crowd-sourced data from social media, limiting real-time sensor integration.
31	[77]	Pattern Recognition and Adaptive signal processing techniques	Limited to wearable and biomechanical sensors; lacks integration with environmental or visual data.
32	[97]	NLP and deep learning classifiers	Limited to voice-based data; lacks real-time sensor-based emergency event detection.

(Continued)

Table 4 (continued)

Sr. No.	References	Algorithms and technique	Research gaps
33	[93]	ML classifiers and network analysis algorithms	Focus on social media data; lacks physical sensor integration and real-time emergency behaviour monitoring.
34	[83]	CNNs, RNNs (LSTM), Transformers and ensemble methods	Broad sensor review; lacks focus on human behaviour classification or real-time sensor networks for emergencies.
35	[85]	Multimodal fusion algorithms and deep learning methods	Data integration-focused; lacks behaviour classification for emergency detection.

RQ5: What are the main limitations and gaps in current research?

This question highlights several limitations which persist across sensing, data quality and modelling dimensions, that can be seen in Table 5. Sensor-related challenges are among the most critical and face robustness issues in uncontrolled environments. Hardware constraints further restrict scalability. Data-related challenges emphasise the lack of comprehensive and diverse datasets. Vulnerable groups such as the elderly and disabled populations remain underrepresented, limiting generalisation to real-world emergencies. Large-scale multimodal datasets are needed to improve robustness, cross-domain adaptability and inclusivity. Model and algorithmic limitations include reliance on computationally expensive deep learning models. The literature indicates that future research must balance model accuracy with interpretability and address data diversity gaps.

Table 5: Research gap table for RQ5: What are the main limitations and gaps in current research?

Sr. no.	References	Limitation	Research gaps
Sensor related limitations			
1	[65]	Background noise and environmental variability affect accuracy. Need for more robust models that generalise better.	Improvement in robustness for different environments.
2	[96]	Inconsistent sensor placement in smartphones leads to variability in behaviour signals.	Better sensor placement and adaptive models.
3	[77]	Calibration and accuracy of WSS devices, user compliance issues and wireless transmission and battery life concerns in field deployment.	Sensor calibration and deployment issues in real-world settings.

(Continued)

Table 5 (continued)

Sr. no.	References	Limitation	Research gaps
4	[89]	Lack of adaptability to unstructured environments; failure to generalise across different factory layouts without manual recalibration.	Generalisation to unstructured environments.
5	[67]	Occlusions and multiple subjects complicate fall detection in crowded settings. Performance degradation without powerful hardware for real-time systems.	Limited scalability and hardware dependency.
6	[68]	Single classifier (k-NN) may not generalise well for complex overlapping activity patterns. Sensor integration in real homes remains a challenge.	Single classifier dependency and sensor integration.
7	[69]	No personalised movement models to account for individual variations. False alarms in real-world trials suggest a need for adaptive systems.	Lack of personalised detection models and false alarm reduction.
8	[70]	Sensor fusion challenges in real-world settings and handling noisy or missing data across modalities.	Sensor fusion issues and data noise handling.
9	[71]	Environmental interference affects RF signal accuracy. Limited generalizability from controlled environments to real-world homes.	Environmental interference and generalisation challenges.
10	[83]	Lack of standardised datasets, cross-domain transferability issues and scalability challenges for ML/DL models in disaster contexts.	Standardisation issues and cross-domain transferability challenges.
11	[84]	Trade-off between decision speed and accuracy and dependency on comprehensive input data for effective evacuation decision-making.	Accuracy vs. speed trade-off and data dependency.
12	[73]	Small sample size, false alarms due to sensor noise and privacy concerns with vision-based systems. Compliance issues with wearable devices.	Sample size limitations and sensor noise causing false alarms.

(Continued)

Table 5 (continued)

Sr. no.	References	Limitation	Research gaps
13	[87]	Availability and quality of multimodal data, weather forecast noise and limitations in prediction accuracy over longer time horizons.	Data quality and noise in environmental data for forecasting.
14	[98]	Dependency on accurate pose estimation, occlusions, lighting conditions and camera angle issues.	Pose estimation challenges due to occlusion and lighting.
15	[74]	Limited real-world fall datasets, complex model embedding on low-power devices and the need for model complexity balancing with energy efficiency.	Limited datasets and model embedding on wearable devices.
16	[63]	Noisy and incomplete sensor data, need for large labelled datasets and challenges in real-time adaptability on mobile/wearable devices.	Data quality and real-time deployment challenges.
17	[62]	Generalisation issues across sensor placements, sensor variability and overlapping activity patterns.	Generalisation issues and deployment in real-world settings.
18	[99]	Balancing accuracy and computational efficiency in wearable devices.	
18	[99]	Discrepancies between simulated and real IMU data, causing domain shift.	Real vs. simulated data discrepancies and computational cost of simulations.
19	[75]	High computational cost of simulation.	
19	[75]	Low-resolution thermal sensors, environmental noise effects and difficulty distinguishing subtle activity differences from thermal data.	Sensor resolution and environmental noise affecting accuracy.
Data challenge			
20	[80]	Data incompleteness and label noise from social media. Lack of model explainability and generalizability in unseen disaster scenarios.	Data quality issues and model transparency.

(Continued)

Table 5 (continued)

Sr. no.	References	Limitation	Research gaps
21	[82]	Occlusion in images, identity switches and ambiguous contexts in disaster images reduce model accuracy. Need for more diverse annotated datasets and lightweight models for real-time applications.	Image occlusions and need for diverse datasets.
22	[97]	Reliance on accurate voice-to-text conversion may fail under noisy environments. Semantic variability in caller statements complicates consistent classification.	Voice-to-text conversion errors and contextual variability.
23	[93]	Incomplete and biased social media data make it difficult to filter misinformation. The reliance on platform-specific behaviour limits the model's effectiveness.	Data bias and platform-specific behaviour challenges.
24	[95]	Small dataset size, privacy concerns with biometric data and challenges in modelling diverse crowd behaviours in real-time.	Privacy issues and diverse behaviour modelling.
25	[91]	Small sample sizes, difficulty obtaining reliable ground truth labels and limited exploration of complex ML models for continuous stress detection.	Small sample size and limited model complexity.
26	[86]	Imbalanced and noisy data from crowd-sourced social media and challenges with GAN-generated synthetic images for multimodal datasets.	Data imbalance and GAN-based data generation issues.
27	[92]	Need for large datasets for training, degradation in performance due to variability in disaster types and cross-domain challenges.	Dataset size and performance degradation in varying disaster contexts.
28	[76]	Loss of temporal information when selecting frames randomly and computational complexity of deep models. Scarcity of datasets capturing complex indoor activities.	Temporal information loss and dataset scarcity.

(Continued)

Table 5 (continued)

Sr. no.	References	Limitation	Research gaps
29	[14]	Limited datasets and lack of detailed categories for vulnerable populations in evacuation scenarios.	Dataset limitations and vulnerable populations are underrepresented.
Model and algorithmic limitations			
30	[81]	Dependency on real-time social media data, which may be unreliable. Scalability of multi-agent RL in large-scale disasters.	Reliability of social media and scalability issues.
31	[85]	Under-explored interactive visualization of multimodal data. Lack of user-centric design and adaptability to dynamic disaster scenarios.	Visualization and user-centric design challenges.
32	[72]	Video quality and camera placement issues affect detection accuracy. Privacy concerns with surveillance footage in public areas.	Video quality and privacy concerns in public settings.

5 Discussion

This systematic literature review has offered a broad overview of human behaviour classification in emergency situations, highlighting the variety of methods, datasets, and challenges within the field. The main aim was to examine how human behaviour classification is implemented across various types of emergencies, for the identification of commonly experimented datasets and sensors, to evaluate the performance of machine learning and deep learning algorithms, and to point out the existing gaps and limitations in current research.

5.1 Key Findings

The reviewed studies cover a wide range of emergency types, including health-related crises, natural disasters, and industrial accidents. Additionally, emergency scenarios like panic detection in crowds, disaster response coordination, and health crises in single-person households were explored. However, despite the wide array of emergencies discussed, several gaps exist in terms of coverage. Many studies focused primarily on falls, especially in elderly populations, neglecting other critical emergencies such as public safety incidents or large-scale natural disasters. The focus on single emergency types restricts the ability of models to generalise to different contexts, which could limit their real-world applicability.

Multimodal Datasets:

The studies involved various multimodal datasets where the common data types are sensor data (from wearables and environmental sensors), images, video footage and social media content (Posts or comments). Social media data is useful but likely to suffer from issues such as incompleteness and bias, which affect the accuracy of the models. If we now consider the sensor-based datasets (such as those derived from accelerometers, gyroscopes and RF sensing), they are promising but frequently encounter

challenges with data fusion, sensor calibration and environmental factors intervention. Most of the datasets are limited to controlled environments, and there is an empty space left for real-time and dynamic datasets capturing real-world emergencies. This limits the ability to generalise findings and apply models in different uncontrolled settings.

Sensors and Technology:

Sensors such as wearable sensors, RF sensing, video surveillance and social media platforms were utilised to detect and classify human behaviour. Many sensors have limitations in terms of accuracy and robustness, particularly in noisy or uncontrolled environments. It is a common observation that RF sensors and video surveillance show sensitivity to environmental interference and often face problems such as occlusions or poor camera placement, respectively; their performance tends to decline in real-world conditions. Issues like user compliance and battery life are usually encountered in wearable devices, restricting their effectiveness in continuous real-world monitoring. The fact that sensors play a crucial role in emergency detection, their integration with multimodal data from social media or environmental sources is still not widely explored.

Machine Learning and Deep Learning Algorithms:

The machine learning and deep learning algorithms used in the studies are quite diverse, with CNNs, LSTMs, SVMs, and Random Forests being the most frequently employed models. These algorithms have proven particularly effective for tasks such as activity recognition (including falls and panic detection) and event classification. Deep learning models like CNNs and LSTMs have demonstrated strong potential in managing sequential and spatial data, whereas traditional ML models such as SVMs and Random Forests are generally applied to simpler classification tasks, as presented in Table 6. Many of these models face significant challenges in terms of real-time applicability, scalability and generalizability to different emergency contexts. For instance, models trained on specific emergency types (like falls or fire accidents) often fail to generalise to broader scenarios, which limits their robustness in handling real-world emergencies. Lack of interpretability in deep learning models can make it difficult to understand model decisions, particularly in critical emergency response situations.

Table 6: Comparative performance table for ML/DL algorithms in human behaviour classification for emergencies

Author	Model/Algorithm	Datasets used	Accuracy (%)	Remarks
[63]	Convolutional neural network (CNN)	UCI-HAR, KU-HAR, WISDM and HMDB51	97.87, 99.12, 96.58 and 98.51	Good for spatial data (e.g., images). Performs well with simple data types but is less effective for sequential data.
[32]	Long short-term memory (LSTM)	UCF11, UCF sports and J-HMDB	98.3, 99.1 and 80.2	Effective for sequential data. Great for capturing temporal dependencies but computationally heavier. Outperforms LSTM in some cases due to bidirectional flow of temporal data, especially useful for sequential event detection (e.g., falls).
[62]	Bidirectional LSTM (BiLSTM)	K-Fall and SisFall	97.93 and 98.99	

(Continued)

Table 6 (continued)

Author	Model/Algorithm	Datasets used	Accuracy (%)	Remarks
[92]	Transformers (ViT)	ImageNet 1kdataset	88.55	Very effective with large, complex datasets; excels in handling long sequences and multimodal data.
[73]	Random forest (RF)	3 (PIR), 2(PIR), 1(PIR) Datasets	98, 96, 87	Effective for classification with smaller datasets. Simple to implement but less powerful for complex sequential or multimodal data.
[116]	Support vector machine (SVM)	Crowdsourced citizen complaints (LAKSA)	89.2	Works well for smaller datasets. Less efficient for large or multimodal data. Often used as a baseline classifier.
[69]	Gradient boosting (GB)	SisFall	99	Performs well in imbalanced datasets. Often outperforms Random Forest and SVM in accuracy and generalisation.
[116]	k-Nearest neighbours (k-NN)	Crowdsourced citizen complaints (LAKSA)	85.2	Simple, non-parametric classifier, but struggles with large datasets and computational efficiency.
[73]	Decision trees (DT)	3 (PIR), 2(PIR), 1(PIR) Datasets	97, 92, 89	Simple model with high interpretability. However, prone to overfitting with complex datasets.
[98]	Naïve bayes (NB)	Custom (1510 Pose Images)	90	Performs well with small datasets and categorical data. May not perform well with high-dimensional or continuous data.
[62]	ConvLSTM-Attentionmodel	K-Fall	92.76	Integrating convolutional and LSTM layers with attention mechanisms. However, sensitivity and specificity metrics were not reported, limiting the holistic evaluation of its effectiveness.

(Continued)

Table 6 (continued)

Author	Model/Algorithm	Datasets used	Accuracy (%)	Remarks
[62]	Ensemble models	SisFall, KFall	98.9, 97.9	Combines multiple models (e.g., CNN, RF, LSTM) for better performance. Helps reduce overfitting and improves robustness.
[14]	YOLO (You Only Look Once)	HBDset	>90	Primarily used for object detection in images. Fast and efficient but less suitable for temporal data.

5.2 Gaps and Future Recommendations

Integration of Multimodal Sensor Data:

Identified gap in this review is the scarce integration of multimodal sensor data. Several studies have employed different sensors, most have not successfully combined these data streams, impacting the accuracy and robustness of the developed models. Future research should focus on fusion techniques which are capable of integrating multiple sensor modalities in real time and allowing for more dependable emergency detection under diverse conditions.

Real World Dynamic Datasets:

There is a strong need for real-world dynamic datasets that cover a wider range of emergencies, including public safety, natural disasters and industrial accidents. Most of the reviewed works rely on controlled settings or simulated data, which may not truly reflect the complexity and diversity of real emergency conditions. Datasets that collect real-time information from real incidents would support better accuracy, scalability and generalisation of the models. Especially, open source multimodal datasets containing different kinds of emergencies should be given priority.

Improved Sensor Technologies:

Sensor technologies encounter significant challenges concerning accuracy, power consumption, and adaptability in different environments. For example, wearable sensors rely heavily on user compliance, whereas video surveillance systems are influenced by obstacles and changes in camera angles. Future studies should aim to develop robust and adaptable sensors that can operate efficiently wherever deployed, provide longer battery life, and remain easy to deploy in real-world settings. Hybrid sensors that combine environmental and human-centred data would further contribute to offering a more holistic understanding of emergency situations.

Hybrid and Explainable Models:

Although deep learning models such as CNNs and LSTMs are widely used, their interpretability remains a significant challenge. In emergency situations, understanding the logic behind a model's decision is crucial, especially when human safety is at risk. Future studies should prioritise integrating explainable AI (XAI) approaches with deep learning models to enhance both transparency and dependability. Combining traditional machine learning techniques with deep learning within hybrid frameworks could also improve the robustness and adaptability of emergency classification systems.

Addressing Privacy and Ethical Concerns:

Several studies have examined the privacy and ethical implications of using personal data in the context of wearable sensors and video surveillance. There is a need to preserve any sensitive data in case of any emergency in order to avoid any potential danger and help maintain the privacy of individuals. There is a need to develop a framework that respects the privacy of the person and ensures that ethical standards are followed because sensor data from personal devices and public areas play a key role in such studies.

5.3 Limitations of Review Study

The areas that need attention include improving real-time detection, enhancing model performance, and making sure that data protection is strong enough to address ethical and privacy concerns in system design. One of the most important issues for this SLR is that the inclusion criteria are limited to studies published between 2020 and 2025, which narrows down the scope of this analysis. Methodologies used in the reviewed studies must also be examined for further understanding of limitations. This analysis lacks broader domains such as emergency planning, disaster response, and preparedness strategies. Another issue that needs attention is the unauthorised use of proprietary datasets and closed methodologies. This can be the cause of unclear direct comparisons of algorithms and reduce reproducibility. The absence of consistent benchmarks and standardised evaluation criteria across the reviewed literature presents an added challenge. These issues, if incorporated, would result in a more robust and trusted system.

6 Conclusion

The review found that HBC has become more accurate with time by the use of advanced sensors, with intelligent machine learning and deep learning models. These models have shown potential in the classification of human behaviour when aided with multimodal datasets. The majority of research still focuses on controlled environments and limited emergency types, indicating that a gap between experimental and real-world performance. One of the major problems is that the existing research only focuses on very few types of emergencies, particularly fall detection in elderly people. Other challenges include small datasets, biased samples, and loosely coordinated sensor setups. In some cases, the integration of different data streams is either weak or missing altogether. Recently, there has been a growing trend to mix different data types like sensors, videos, and even social media posts. Many studies still rely on datasets created in controlled environments, which do not represent the real emergency conditions. Most of the current research is dependent on wearable devices like accelerometers, gyroscopes, or RF sensors. Their dependency on user cooperation becomes a limiting factor. Social media and video surveillance, in some cases, may not always give real-time or ground-level detail. Dependency on the intelligence of the models and how well we understand their outputs is also an important factor that cannot be ignored for making such systems.

For future needs, it is necessary to concentrate on generating richer, real-world datasets and optimizing multimodal integration between different datasets, such as sensors, vision, and social media data. There is a Need to make these systems explainable, observing privacy concerns, and ethically grounded for deployment in actual emergency scenarios. The need for focus is in several key areas, such as the nature of emergencies under consideration, including the role of diverse types of datasets or sensors, and how machine learning or deep learning techniques are proving their abilities in this context.

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