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Applications of Artificial Intelligence and Machine Learning in Disasters and Public Health Emergencies

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Abstract

Indexed literature (from 2015 to 2020) on artificial intelligence (AI) technologies and machine learning algorithms (ML) pertaining to disasters and public health emergencies were reviewed. Search strategies were developed and conducted for PubMed and Compendex. Articles that met inclusion criteria were filtered iteratively by title followed by abstract review and full text review. Articles were organized to identify novel approaches and breadth of potential AI applications. A total of 1217 articles were initially retrieved by the search. Upon relevant title review, 1003 articles remained. Following abstract screening, 667 articles remained. Full text review for relevance yielded 202 articles. Articles that met inclusion criteria totaled 56 articles. Those identifying specific roles of AI and ML (17 articles) were grouped by topics highlighting utility of AI and ML in disaster and public health emergency contexts. Development and use of AI and ML have increased dramatically over the past few years. This review discusses and highlights potential contextual applications and limitations of AI and ML in disaster and public health emergency scenarios.

According to the World Health Organization (WHO), a "public health emergency" is defined as an event or occurrence that threatens the health of the public and poses substantial risk.[1] Such emergencies can include natural disasters, disease outbreaks, or bioterrorism. Responding to a public health emergency requires rapid decision-making and efficient communication of information between government agencies, response organizations, and healthcare facilities. Understanding situational risk, strengthening governance, enhancing preparedness for effective response, and investing in measures to enhance resilience are all critical aspects of disaster risk reduction. The Sendai Framework for disaster risk reduction established by the United Nations aims to substantially reduce global disaster mortality, reduce direct disaster economic loss, and substantially reduce disaster damage to critical infrastructure and disruption of basic services by 2030.[2] In this vein, prediction/forecast models and preplanned protocols, such as evacuation planning, have been used to mitigate the consequences associated with these events. With the rise of artificial intelligence (AI) and machine learning (ML), monitoring of information during emergent situations and decision-making under time-sensitive conditions have significantly enhanced the potential to predict the spread of disease, develop more efficient evacuation plans, and assist in the distribution of resources to areas in need.

ML models are typically trained on large quantities of representative data for the target task and subsequently applied to unseen test data without a requirement for explicit programming and handcrafted decision boundaries. During the training process, these algorithms normally perform iterative updates to parameters of the model, which is then used to make predictions and improve at achieving the desired task over time.[3] Comparatively, ML is similar to statistics in that both fields can be used, in principle, to make inferences or predictions. However, statistical models are better suited to infer relationships between variables, whereas ML algorithms concentrate on making predictions.[4] Table 1 describes typical AI/ML algorithms along with terms that may not be familiar to the disaster and public health emergency response community, defined in the order in which they appear in this review.

This review aims to highlight recent developments in intelligent computing for disaster and public health emergency scenarios. It will focus on the potential applications and limitations of AI and ML in emergency evacuation, emergency management and decision-making, information processing, and mass casualty prevention.

Table 1. AI and ML terms defined in the order that they appear in this review

Term	Definition
Random forest	An ensemble machine learning algorithm that combines multiple learners in the form of nodes and predictors.[5]
Deep learning	A method of machine learning that makes use of large neural networks. The adjective "deep" comes from the use of multiple layers in a network.[6]
Ant colony optimization (ACO)	A population-based optimization algorithm where artificial agents work to solve problems as efficiently as possible by mimicking the behavior of real ants.[7]
Reinforcement learning	A learning paradigm that is concerned with how intelligent agents ought to take actions in an environment in order to maximize the notion of cumulative reward.[8]
Adaptive boosting	A machine learning meta-algorithm that combines other learning algorithms into a weighted sum that represents the final output of a boosted classifier.[9]
Gradient boosting	A machine learning technique for regression and classification problems. Produces a prediction model in the form of an ensemble of decision trees.[10]
Ensemble learning	Multiple learning algorithms used to obtain a better predictive performance than could be obtained from a single constituent learning algorithm.[10]
Constraint programming model	A paradigm used to solve combinatorial search problems in which the user establishes constraints and the constraint solver finds a solution to them.[11]
Hierarchical task network planning	An AI approach to automated planning in which a hierarchical structured network can give actions to solve a series of tasks.[12]
Fuzzy logic	A logical concept concerned with the formal principles of approximate reasoning in which degrees of truth of variable values may be any real number between and including 0 and 1.[13]
Semi-supervised learning	An approach to machine learning that combines labeled data with unlabeled data during training.[6]
Artificial intelligence of things	A network in which sensors and actuators blend into the human environment and information is shared across platforms in order to develop a common operating picture.[14]
Binary decision tree	A structure that serves as a compressed representation of sets or relations. It is often associated with 'Boolean functions' in computer science, or a graph with several nodes.[15]
Supervised learning	An approach to machine learning that uses labeled data.[6]
Active learning	An approach to machine learning in which the learning algorithm can interactively query a user to label new data points with desired outputs.[6]

Methods

For the purposes of this review, identification of viable sources[19-37] followed the methodology of Fernandez-Luque and Imran[16] and Lamy et al.[17] The methodology was selected because it was applied to a parallel review that examined the use of AI and social media in humanitarian crises.[16]

The 2 databases included were PubMed and Compendex to encompass potentially relevant articles from the public health and engineering fields, respectively. For PubMed, the following search terms were used, with priority being placed on the terms ("Artificial Intelligence" OR "Machine Learning"). Several Medical Subject Headings (MeSH) terms were also used to ensure that the topic of "Natural Disasters" was completely encompassed in the search (Table 2). Additional manual searches of cited references were cross-referenced with the primary search to capture all potential sources that pertained to the desired topic. For Compendex, the following search terms were included (Table 3), with priority being placed on the terms ("Artificial Intelligence" OR "Machine Learning").

Data Sources and Inclusion/Exclusion Criteria

According to the 2018 Artificial Intelligence Index, the current generation of AI research really began to take hold in 2013. This follows a major breakthrough for deep learning when researchers were able to drastically reduce the error in large-scale image recognition. Focusing upon the most recent advancements in AI, inclusion criteria captured English language papers published within the past few years (2015-2020) with available full text pertaining to AI relevant to disasters or public health emergencies. As the application of AI and ML in disaster and public health emergency contexts had not yet been sufficiently developed, articles before the search period were excluded (Figure 1).

Article Selection Process

Articles that met inclusion criteria were filtered iteratively by title screening followed by abstract review and full-text review. Articles were organized according to the following unique categories: Emergency Evacuation, Emergency Management and Decision-Making, Information Processing, and Violent Mass Casualty Event Response.

Selected articles with the greatest novelty and highest relevancy in their respected subcategory were highlighted to identify unique approaches and the breadth of potential AI/ML disaster and public health emergency applications. The selection process followed the PRISMA review article selection methodology and flow diagram.[18]

Results

A total of 1217 articles were initially retrieved by the search. Upon relevant title screening, 1003 articles remained. Following abstract screening, 667 articles remained. Full-text review for relevance yielded 202 articles. A total of 56 articles met inclusion criteria. From the final articles identified based on sufficient applications of AI/ML in disaster responses, several representative articles were highlighted in each of the organizational categories: Emergency Evacuation, Emergency Management and Decision-Making, Information Processing, and Violent Mass Casualty Event Response, encompassing a total of 17 articles.

Emergency Evacuation

During natural disasters, emergency evacuation considerations are ever-present. However, evacuation routes can be easily overwhelmed, and the safety and efficiency of the evacuation plan rely heavily on organization and cooperation. While modeling is often used to predict the best evacuation routes, these predictions often

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Table 2. Pubmed search queries

Search no.	Query	No. of results
1	*((((“artificial intelligence”) OR “machine learning”) OR “intelligent computing”)) AND “Natural Disasters“[Mesh]*	14
2	*(“emergency preparedness”) AND (((“artificial intelligence”) OR “machine learning”) OR “intelligent computing”)*	2
4	*(((terror*) OR casualty)) AND (((“artificial intelligence”) OR “machine learning”) OR “intelligent computing”)*	24
5	((“artificial intelligence“[Title/Abstract] OR “Machine Learning“[Title/Abstract])) AND Mass casualty	4
6	*(((((Natural disaster) OR Hurricane) OR Flooding) OR Earthquake)) AND (((“artificial intelligence”) OR “machine learning”) OR “intelligent computing”)*	61
7	*((“Artificial Intelligence“[Title/Abstract] OR “Machine Learning“[Title/Abstract])) AND emergency) AND “social media”*	10
	Total	115

Table 3. Compendex search queries

Search no.	Query	No. of results
1	*“artificial intelligence” or “machine learning” AND “emergency preparedness”*	2
2	*“artificial intelligence” or “machine learning” AND “natural disasters”*	71
4	*“artificial intelligence” or “machine learning” AND “casualty”*	157
5	*“artificial intelligence” or “machine learning” AND “terrorism”*	18
6	*“artificial intelligence” or “machine learning” AND “mass shooting” OR “school shooting”*	114
8	*“artificial intelligence” or “machine learning” AND “public health emergency”*	10
9	*“artificial intelligence” or “machine learning” AND “incident command”*	157
10	*“artificial intelligence” or “machine learning” (subj, abstract, title) AND “decision making” AND “emergency preparedness”*	81
11	*“Artificial Intelligence” OR “Machine Learning” AND Emergency AND “social media” AND (2020 OR 2019 OR 2018 OR 2017 OR 2016 OR 2015)*	281
12	*“Artificial Intelligence” or “Machine Learning” AND Emergency AND “information processing” AND (2019 OR 2018 OR 2017 OR 2016 OR 2015)*	173
13	*“Artificial Intelligence” or “Machine Learning” AND “emergency evacuation” AND (2019 OR 2018 OR 2017 OR 2016 OR 2015)*	38
	Total	1102

lack the ability to simulate the behavior of people during emergency situations.

ML has been used to model pre-evacuation decision-making. Using random forest to model and predict people’s emergency behavior pre-evacuation, 1 study[19] aimed to investigate the factors influencing decision-making in the evacuation process. The results showcased that random forest provides rich behavioral interpretations of evacuees by automatically capturing interactions among independent variables and nonlinearities between the independent variables and the outcome. Applying their model to investigate fire evacuations, the researchers were able to illustrate how social and physical factors (such as seat of the evacuee and group size) can influence the pre-evacuation decision-making process. With these interpretations, policy-makers and emergency managers can extract useful insights to develop more effective evacuation plans. This model has been shown to provide more accurate results than the traditional approach (ie, logistic regression).

ML methods have also been used to recognize overall behavior of an evacuating crowd. By detecting the status of crowd flow and estimating the occurrence of anomalies during evacuation such as congestion of evacuation routes or concentrated directional movement, deep learning was used to forecast crowd behavior under evacuation settings.[20]

To optimize evacuation, ML can calculate the best routes and develop mathematical solutions to issues associated with varying evacuation parameters. Bagloee et al. discussed the issue of contraflow, the changing of directions of roads as a traffic control measure to streamline emergency evacuation. Using an ML algorithm tailored to the actual traffic network of the city of Sioux Falls, the most efficient traffic evacuation pathway was calculated based on a “budget” of roads that could be made contraflow. The application of this technology could render planning of traffic evacuation routes easier and faster.[21] This model uses a hybrid of ML and optimization algorithms, which was found to outperform some other ML-exclusive algorithms.

A common algorithm used for evacuation route computation is the ant colony optimization (ACO) algorithm. In 2014, ACO was used to calculate the best routes for an evacuation in a tsunami crisis. The model was validated by conducting 2 drills in the coastal town of Penco, Chile, which was affected by a massive earthquake and tsunami in 2010. The first drill was held with release of minimal information during which the population acted intuitively. The second drill was conducted using information provided by the model, channeling people to optimized routes generated by the ACO algorithm. These results showed that in the event of an emergency, conventional evacuation routes had longer escape times compared with those identified by the developed ACO model.[22] On a smaller scale, AI algorithms can be used to direct evacuations from buildings and other populated venues. A separate research team used ACO to find the shortest escape route from a building in the event of a fire, taking into consideration temperature at the fire site, smoke concentration, and carbon monoxide concentration.[23] While both projects indicate reduced evacuation time using ACO, these prototypes do not consider other environmental factors like ease of accessibility of roads or damaged infrastructure, which can significantly impact the determination of the safest routes in tsunami and fire evacuations. Furthermore, for all aforementioned papers, these algorithms require extensive mapping of terrains for practical application in real-life situations.

Emergency Management and Decision-Making

ACO has also been used for emergency management and distribution of resources in disaster situations to overcome the vehicle routing problem presented during the distribution of emergency resources. One algorithm was designed to find feasible solutions to quickly and efficiently deploy resource vehicles.[24] A mathematical optimization model proposed by Wang et al. used a new ACO-based algorithm, which incorporated the idea of a virtual central “depot,” or resource distribution center for distributing emergency

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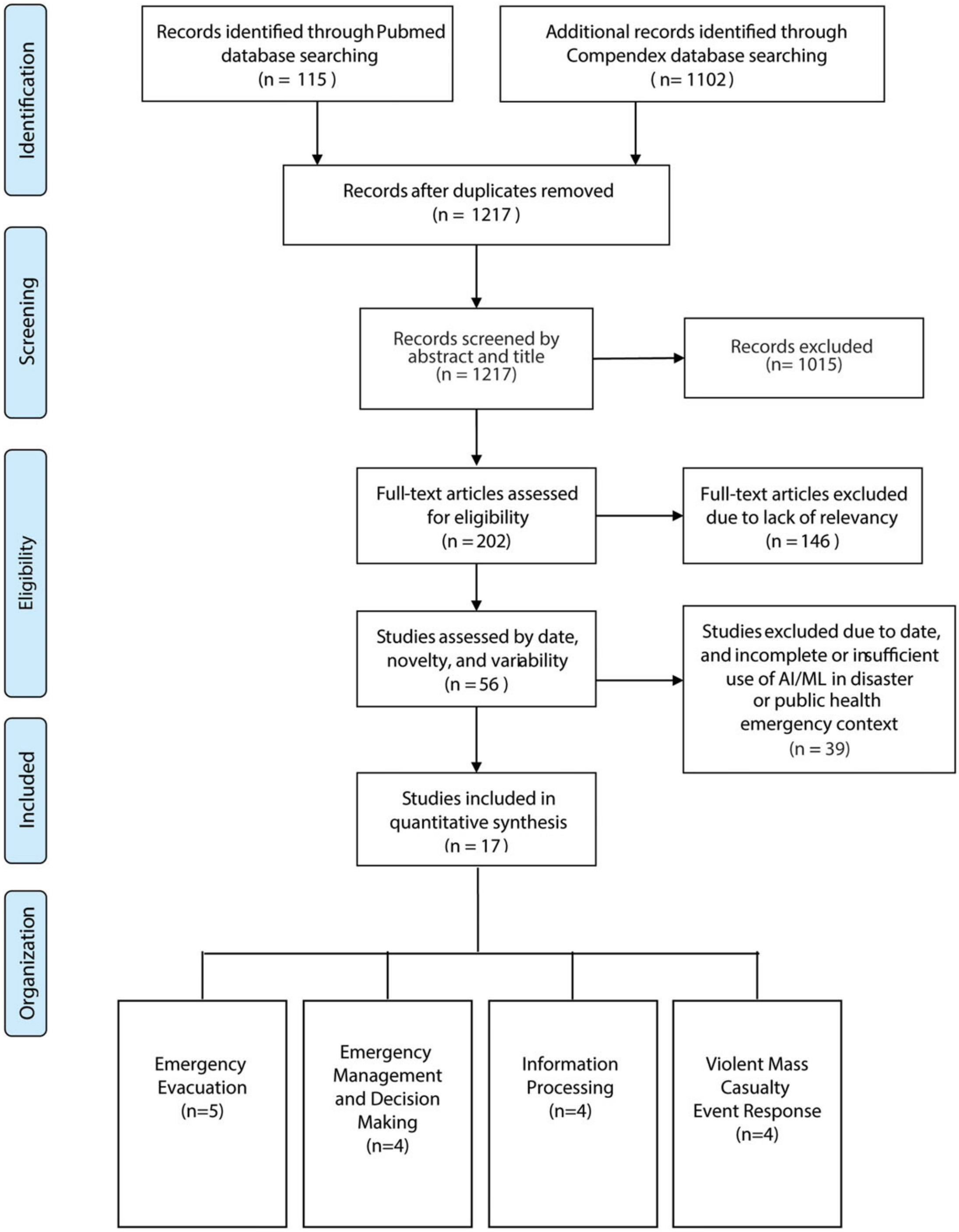

Figure 1. Study flow diagram.

resources from a stock center during an emergency. The proposed algorithm proved more efficient than previous vehicle routing problem optimization models, calculating the best routes in 29 of 33 events (88%).[24] Despite its efficiency, this project does not account for traffic blockages or other disruptions that could affect the results of the model.

Rapid response in emergency situations is undoubtedly critical. Accordingly, the rapid calculative ability of ML algorithms can be useful in establishing decision support systems that aid in the development of emergency response plans and can be embedded into an emergency command decision support system. Hierarchical task network planning is an AI planning technique used to search for a solution to obtain an initial task network in the early state. This tool, adapted for the rapid development of emergency response plans, the coordination of agencies involved in disaster scenarios, and the preparation of standard operation procedures, was implemented in a case of typhoon evacuation. The results showed that the intelligently generated decision-making model was flexible and capable of replicating the dynamism and temporal uncertainty in emergency response situations.[25]

Although this model is an extremely useful tool, it cannot be used in the absence of emergency managers. Like most models discussed, this decision support paradigm is designed to support emergency response personnel and improve their ability to make timely decisions.

Lopez et al. implement a coordinated decision-making agent for emergency response scenarios. Agent implementation uses reinforcement learning, an ML technique that enables an agent to learn from experimenting. For proof of concept, the researchers created a simulation of an emergency situation and the agent was tasked with allocation of resources in a way that maximized the number of people treated at the hospital. The results showed a significant increase in decision-making speed when compared with past projects performed by the same research team.[26] Implementation of multiple ML agents in the same model could be a strategy used for more complex cases.

In contrast with traditional ML methods, deep learning techniques are modern ML approaches that have been on the rise. Such deep learning techniques have been used to classify images to identify survivors in debris after an earthquake. Although decision-making during emergency scenarios is often difficult because of the lack of actionable information, the application of deep learning allows for the classification of image data obtained from smart infrastructures with significantly higher accuracy and the use of less time and computational resources compared with traditional ML approaches. Specifically, this research uses convolutional neural networks and heterogeneous data sources to match the allocation of emergency resources to individuals in extreme need. The results showed that deep learning approaches handled noise in data much more proficiently than their traditional ML counterparts.[27] One limitation of this approach is the inability of the classifiers to identify text data. Such data are addressed more thoroughly in the next part of this review.

Information Processing

With the rise of social media, information processing to acquire and decipher potential public health hazards has become an important tool. Microblogging platforms such as Twitter enable real-time tracking of events through immediate user updates. In the case of crisis, reports of casualties, infrastructure damage, and urgent needs on these social networks can provide important information in the first few hours of an event, which can help significantly reduce both human loss and economic damage. Recently, a research group used an ML approach to tag and label data derived from tweets that were shared during emergency scenarios. Using this system, they were able to identify tweets that were relevant to disaster response efforts.[28] This filtering tool makes use of online ML, which processes data as a sequential stream, allowing for updating of the model continuously as new labeled data become available. Such a tool can help to appropriately alert humanitarian organizations and first responders to pertinent information during disaster situations. Nevertheless, access to data in this system is limited by social media tokens (ie, Twitter allows 450 queries per 15 min on their search API).[28] Thus, the speed at which data are tagged and classified may not be optimized due to this constraint.

Filtering of information provided by social media during emergencies is not uncommon. In fact, while Twitter and other microblogging platforms have the capacity to provide up-to-date data, information overload is often prevalent. A study published in 2020[29] aimed to use different ML algorithms to analyze heterogeneous social media data, that is, data that encompass many different types of emergency and disaster scenarios as opposed to just focusing on one. In heterogeneous datasets, both training and test data are drawn from multiple data sources, which makes it difficult for the learning algorithm to generalize. Using ensemble learning algorithms (Adaptive Boosting, Gradient Boosting, and Random Forest), researchers were able to classify relevant text-based Twitter messages that were disaster-related or informative and contributing to situational awareness. The results showed that ensemble learning algorithms were much better at classifying heterogeneous data than nonensemble learning algorithms. This research is among the first to tackle the massive diversity of real-world social media data. As a result, classifying such data is often difficult and produces inaccurate or ambiguous results. Over time, it is anticipated that improvements in the field of AI will allow for these hurdles to be overcome.

Airborne (eg, National Oceanic and Atmospheric Administration aerial) and spaceborne (eg, Maxar WorldView) imaging systems are often used during emergency situations to map the extent of postevent damage, but the delay between an area being affected and image acquisition can sometimes be longer than the desired time window for making critical resource deployment decisions. In addition, 4/8-band multispectral imagery (MSI) is unable to see through clouds, which typically obscure areas affected by hurricanes. For this reason, there has been growing interest in Synthetic Aperture Radar (SAR) imaging systems, as they are capable of seeing through clouds. However, SAR images can be difficult to interpret without proper training and can have inadequate resolution for certain tasks when captured by satellites. When noncloudy overhead MSI and RGB imagery is available, it can be very useful for identifying flooded areas, damaged buildings, and obstructed roads. Recently, there have been efforts to automate these tasks with deep learning, as these are very time-consuming to perform manually. One of these is the xView2 challenge,[30] which focuses on building damage assessment on images from the DigitalGlobe Open Data Program[31] for 6 different disaster types, in which buildings are designated with varying damage labels ranging from no damage to completely destroyed.

While the former approaches focus on streamlining the use of satellite imagery, inclement weather can render satellite imagery nonfunctional. In a project titled Evolution of Emergency Copernicus services (E2mC), crowdsourcing approaches were coupled with a pre-established emergency management system to obtain temporal and spatial information derived from social media using digital volunteers and local eyewitness reporters. This witness system is coupled with a social media ML filtering system to provide the most complete depiction of the emergency scenario at hand with as few gaps in information as possible. The ML component can preprocess the social media posts to decipher slang and predict the relevancy of the post. This information processing system can generate a damage assessment that may not be available from satellite signals because of inclement weather and can also help constrain and prioritize the imagery ML models process. This system works in tandem with the established emergency management system by providing information on the situation so that experts can implement and make decisions.[32] However, it is still unable to produce information in real-time. While the system can provide information within the first few hours of an event, emergencies require immediate, real-time response to optimally mitigate damage and loss.

Violent Mass Casualty Response

During violent mass casualty events, quick and immediate action is required to secure the safety of those present. With events ranging from active shooter situations to terrorist attacks, the number of injured can readily overwhelm first responders. In 2018, a classification model for survival prediction was designed with the ability to quickly and precisely triage victims by means of wearable devices in the absence of medical personnel. Logistic regression statistical analysis was used to analyze vital signs and classify injury severity. When applied to 460,865 sample cases, logistic regression, random forest, and neural network algorithms were all found to perform best with the "consciousness index," a coma scale independently developed by the team.[33] Limitations imposed by innate bias of the dataset present with any study involving ML are acknowledged. This bias is further detailed in the discussion section. Most of the datasets from this study were collected from patients sustaining accidents in daily life rather than in a disaster context. The deficiency of samples collected from the patients in a disaster is a key limitation of this study.

In conjunction with streamlined triage are efforts toward prevention of violent mass casualty events themselves. In recent years, the United States has seen an alarming increase in active shooter events.[34] AI systems with the purpose of mitigating damages and loss of life in these events have been created. Using an AI interface and virtual events, 1 research team aimed to train school teachers and administrators on what to do in the event of a school shooting. Griffith et al. crafted an accessible game module where teachers can direct students by issuing commands during an active shooter scenario. Users can occupy roles such as teachers, staff and administrators, law enforcement officers, school resource officers, and the suspect role. This ensures that role-players can navigate the scenario without knowing exactly how the students will react.[35] While this training game can help teachers prepare for school shootings, it remains very challenging to emulate the real world and prepare teachers for the trauma of an actual active shooter event. The extent to which a game, even with realistic responses, can prepare teachers for such events remains limited.

AI can also be incorporated into public buildings to improve evacuation routes during an active shooter situation. One example is the use of an "Internet of Things" based decision support system to evacuate civilians during indoor mass shooting events where users are alerted and directed to the safest exits during an emergency. This system uses 3 agents: a threat detection agent that acts as gunshot detectors and accepts human-input data of the assailant's location, a room monitor agent that estimates populations in each room and manages the actions of the doors, and door agents that serve as exit doors or room doors. The threat detection agents locate gunshots and contacts the room monitor for determination of shot origin. The governing room monitor is responsible for initiating and ending the signaling process. The room monitor communicates with the exit doors. Throughout the situation, the door agents continually assess safety levels depending on the proximity of the shooter. This system was applied to a case study of the Pulse Night Club.[36] This combination of Internet of Things and AI (namely "Artificial Intelligence of Things") allows for intelligent decision-making but still requires further testing.

There are also other tools to address deliberate violent mass casualty events. WISER (wireless information system for emergency responders) is a free application on iOS and Android developed by the National Library of Medicine to assist emergency responders in hazardous material incidents. To optimize this tool for the identification of chemical agents (ie, chemical warfare or terrorism events), ML algorithms were developed with functionality similar to WISER with the capacity to identify chemical agents based upon presenting symptoms. This study showed that ML binary decision trees and artificial neural networks were more efficient and more accurate at determining the culprit chemical agent than WISER.[37] However, the ML algorithms experienced decreased efficiency as more symptoms and parameters were added, exemplifying a key limitation in this study (Table 4).

Discussion

While the applications of AI/ML seem ubiquitous, many limitations to current AI/ML systems exist. To currently validate most ML models, large-scale data sets with representative test sets are typically required to serve as a benchmark. Because the foundation of ML relies on the recognition of patterns in data sets, situations that lack robust data are difficult to validate. While many of the referenced articles demonstrate performance at a level of statistical significance, accuracy of particular algorithms falter when more variables are introduced and can over-fit to the bias of a training set. For example, the work by Kaufhold et al. labeling social media data is not only limited by speed, but also by the expansiveness of social media, which increases ML susceptibility to bias. This study addressed several variables, such as relevancy, subjectivity, and objectivity of user tweets but could not account for all possible variables when labeling data.[28] One approach by Pekar et al. uses ensemble learning to mitigate this bias effect observed in large data sets with many variables.[29]

ML bias because of training, learning, and re-learning often reinforces such biases within given datasets. This is true for any project in which ML algorithms are used. Unfortunately, many of the aforementioned articles do not address such biases, which must be acknowledged when reviewing their accuracy and validity. On the other hand, the triage algorithm of Kim et al. does address the bias of their dataset, which relied solely on injury data from daily accidents rather injuries from disaster contexts.[33]

Similarly, to the model by Boltin et al. for the identification of chemical agents showed promising results when the number of symptoms is limited. Given only 9 symptoms, the ML algorithms can identify the involved chemical agent with extreme precision. However, as the number of symptoms increases, the accuracy of the algorithm decreases. The introduction of increased variables can confuse the algorithm, yielding less fruitful results.[37]

It is this uncertainty associated with many of these algorithms that have prevented them from being widely used in the field of public health. Considering that the rise of AI is a relatively recent phenomenon, AI models are still continually being improved upon and novel uses of AI are introduced every year, as observed in the work by Horii et al. on emergency evacuations.[20]

In fact, the vast majority of information processing search results focused on the applications of social media data for emergency situations, a trend that shows researchers are making use of the vast amounts of information made accessible by the Internet. While this abundance of information can be helpful, there remains a lot of noise associated with social media-derived data. Even though ML does an excellent job in filtering out many irrelevant posts, the data extracted from these ML modules may still remain incomplete. As a result, crowd-sourcing and human participation are required to fill in the gaps of information, as seen in the E2Mc analysis system.[32]

Table 4. Summary table of papers discussed and their respective algorithms and applications

Paper	Algorithm(s)	Topics/problems addressed
[19]	Random forest	Emergency evacuation: investigate factors that can influence the pre-evacuation decision-making process.
[20]	Deep learning	Emergency evacuation: recognize overall behavior of an evacuating crowd.
[21]	Supervised (regression) learning	Emergency evacuation: find the optimal traffic evacuation route in a disaster scenario given a "budget" of contraflow roads.
[22]	Ant colony optimization	Emergency evacuation: calculate the best routes for evacuation in a tsunami crisis.
[23]	Ant colony optimization	Emergency evacuation: calculate the best routes for evacuation in the event of a fire
[24]	Ant colony optimization	Emergency management: determine the optimal routes for distribution of emergency supplies in disaster-stricken areas.
[25]	Hierarchical task network	Emergency management: develop emergency response plans and consider the best course of action in typhoon events.
[26]	Reinforcement learning	Emergency management: allocate hospital resources to maximize the number of people treated after an emergency situation.
[27]	Deep learning (convolutional neural networks)	Emergency management: identify survivors in debris after an earthquake to determine allocation of emergency resources to individuals most in need.
[28]	Supervised learning	Information processing: Filter tweets based on information that may be pertinent to first responders during an emergency.
[29]	Ensemble learning (adaptive boosting, gradient boosting, random forest)	Information processing: Classify relevant text-based tweets as informative during a disaster situation.
[30]	Deep learning	Information processing: Automate the processing of Synthetic Aperature Radar imaging.
[32]	Semi-supervised topic modeling	Information processing: Provide a damage assessment by analyzing tweets in the event satellite signals fail to provide clear images.
[33]	Random forest	Casualty response: Triage victims via wearable devices in the absence of medical personnel.
[35]	Adaptive/intelligent behaviors in non-player characters	Casualty response: Simulate an active shooter event in a virtual setting to train schoolteachers and administrators.
[36]	Artificial intelligence of things	Casualty response: Alert civilians during indoor mass shooting events to the nearest and saftest exit.
[37]	Binary decision tree	Casualty response: Identify a culprit chemical agent based on presenting symptoms

Although applications of AI in public health are not yet entirely self-sufficient, these algorithms remain highly versatile and can be potentially implemented in many different areas. Different emergency situations require different tools and modes of action, as depicted by the varying applications of AI in emergency situations. However, many of these systems can be adapted to address other public health emergency categories. For instance, while satellite images using AI can be used to assess damage after natural disasters, they can also be applied during terrorist or violent mass casualty events.

Some interesting trends were revealed. While several articles pertained to issues affecting developed nations (ie, active shooter events in the United States), many others were pertinent to developing nations, especially related to natural disaster events, as similarly noted by Fernandez-Luque and Imran in their review of humanitarian health computing.[16]

Certain limitations of this review are acknowledged. Due to the expansiveness of the public health and AI fields, the search strategy, despite its thoroughness, could not encompass all possible search terms. Accordingly, it is possible that certain relevant articles may not have been captured due to limitations of the search terms used. As only publicly available published works were considered, tools in development and military-based, classified, or other proprietary technologies in use in this field may not have been included. AI used in other fields potentially applicable to the disaster medicine and public health emergency context is beyond the scope of this review. Future directions for AI in this field include further validation of established algorithms, expansion of variables incorporated into these models, application in relevant contexts, and evaluation of practical implementation of these systems.

Conclusions

Disasters and public health emergencies are often complex incidents that require extensive cooperation, resources, and efficient response. This review study highlights various machine learning and artificial intelligence projects applied to the field of disasters and public health emergencies. Ranging from social media data extraction to video games designed to train and prepare teachers for traumatic events, the versatility of AI holds considerable promise. Generally speaking, although AI and ML potentially can be used to address many concerns, there are limitations to overcome in terms of the accuracy and certainty of these systems. In the future, it is expected that AI and ML will be more broadly, consistently, and robustly applied to these practical challenges in disasters and public health emergency contexts.

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