Open Journal of Applied Sciences, 2025, 15(5), 1245-1257
https://www.scirp.org/journal/ojapps
ISSN Online: 2165-3925
ISSN Print: 2165-3917

Application Research of Machine Learning in Emergency Field

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How to cite this paper: Jiang, W. and Liu, X.Q. (2025) Application Research of Machine Learning in Emergency Field. *Open Journal of Applied Sciences*, **15**, 1245-1257.
https://doi.org/10.4236/ojapps.2025.155086

Received: April 2, 2025
Accepted: May 16, 2025
Published: May 19, 2025

Abstract

With the rapid development of science and technology, artificial intelligence plays a significant role across various domains. In recent years, frequent occurrences of natural disasters and human-made accidents have brought increasing attention to emergency management, which constitutes an integral part of China's governance system. As a crucial tool for data analysis and prediction, machine learning has been extensively applied in emergency management. Through bibliometric analysis using CiteSpace software—examining annual publication volumes, authors, and keywords in literature related to machine learning applications in emergency contexts—it is evident that machine learning, as a core AI technology, has been widely utilized in areas such as data analysis, predictive modeling, and decision-making assistance. The integration of machine learning with emergency management can substantially enhance operational efficiency. This paper explores the application research of machine learning in emergency management and investigates its potential to improve emergency response effectiveness while mitigating disaster-related losses.

Keywords

Safety Engineering, Machine Learning, Data Analysis, Artificial Intelligence

1. Introduction

Emergency Management refers to the emergency measures taken to protect people's lives and property, maintain social order, and ensure stability in the face of natural disasters, accidents, or other crises. It should encompass the entire lifecycle of incident management—pre-incident, during-incident, and post-incident phases—including dynamic processes such as monitoring and prediction, coordinated response actions, resource allocation, and recovery and reconstruction [1]. Effective emergency management relies heavily on processing vast amounts of historical data and analyzing real-time monitoring information, necessitating the digitalization of emergency management systems.

Since the establishment of China's Ministry of Emergency Management, the rapid advancement of artificial intelligence (AI) has made the integration of AI with emergency management an inevitable trend. Incorporating AI technologies into emergency management systems can significantly enhance operational efficiency. Machine learning (ML), a core AI technique for data analysis, plays a pivotal role in fields like image processing and computer vision. For emergency management, achieving visualization—through technologies such as facial recognition, video surveillance, object detection, and feature identification—is crucial [2]. These technologies enable early disaster prediction and rapid post-disaster response.

Efficient emergency management also depends on seamless information flow. Building an emergency management digital platform requires machine learning to collect disaster data, analyze samples, and train models for accurate prediction. While advancing digitalization, China must integrate international best practices with its unique national conditions to develop targeted, high-efficiency measures that improve incident response accuracy and reduce disaster losses.

This study employs CiteSpace visualization analysis software to statistically analyze relevant literature from the CNKI (China National Knowledge Infrastructure) database. By examining annual publication volume, contributing authors, and keywords, it reveals the evolutionary trajectory and research hotspots of machine learning applications in emergency management, highlights the advantages of specific machine learning algorithms in particular emergency scenarios, and identifies the current research limitations and future trends in this field.

2. Machine Learning

Machine learning is an interdisciplinary field that integrates disciplines such as statistics, probability theory, and approximation theory. This technology focuses on enabling computers to mimic or autonomously achieve human-like learning behaviors, allowing machines to acquire specific knowledge and skills through its application.

In recent years, with the rapid advancement of artificial intelligence, machine learning—as a critical tool in AI—has seen significant progress in areas such as facial recognition, license plate recognition, and video surveillance. When integrated with emergency management, machine learning algorithms have been increasingly applied across diverse emergency scenarios. These algorithms have proven highly effective, driving emergency management systems to transition from passive defense to intelligent proactive prevention. This shift encompasses end-to-end prevention strategies, spanning risk prediction, real-time response, and post-event recovery.

2.1. Supervised Learning

Supervised learning refers to a paradigm where an algorithm is provided with a labeled dataset containing input data and corresponding target values (correct answers). Through iterative training on these samples and their associated labels, the algorithm establishes relationships between input features and output mappings [3]-[5]. By learning from labeled data, the machine aims to predict outcomes for new, unseen data [6]. A simplified workflow of supervised learning is illustrated in **Figure 1**.

Figure 1. The simple process of supervised learning.

Supervised learning primarily encompasses regression and classification. Regression predicts continuous numerical outcomes, while classification predicts discrete categorical labels. Regression algorithms are mainly divided into logistic regression and linear regression, whereas classification tasks are categorized into binary classification (two classes) or multiclass classification (multiple classes) based on the number of target categories. Regression models are typically applied to problems where the output variable is a real-valued quantity, whereas classification models categorize the output variable. The three core components of supervised learning are models, strategies, and algorithms.

In real-world applications, supervised learning is widely used in scenarios such as spam SMS filtering on mobile devices and spam email detection in email systems. These tasks rely on training models using historical human-labeled data (e.g., user-marked spam messages) to predict whether newly received messages or emails are spam

2.2. Unsupervised Learning

Unsupervised learning utilizes unlabeled datasets for training, where sample data lacks predefined "correct answers." Unlike supervised learning, the machine does not analyze input-output mappings but instead identifies inherent patterns within the data to classify or cluster samples. The simplified workflow of unsupervised learning is illustrated in **Figure 2**.

In contrast to supervised learning, which relies on labeled data with clear target outcomes, unsupervised learning operates without labels. Supervised learning has well-defined objectives and measurable performance criteria (e.g., accuracy), whereas unsupervised learning lacks standardized evaluation metrics due to its exploratory nature.

Unsupervised learning primarily addresses dimensionality reduction and clustering tasks. Dimensionality reduction aims to simplify data complexity while preserving critical structural relationships. Classic dimensionality reduction algorithms include:

- Principal Component Analysis (PCA): A multivariate statistical method that constructs orthogonal principal components to capture key variances in data.

PCA simplifies complex problems by reducing variables to fewer dimensions with minimal information loss [7] [8].

- Factor Analysis: Identifies latent variables ("factors") by analyzing correlations or covariance matrices among observed variables. These factors represent underlying patterns in the data [9] [10].
- Independent Component Analysis (ICA): Seeks a nonsingular transformation of multivariate data to maximize statistical independence among components, often used for source separation [11].

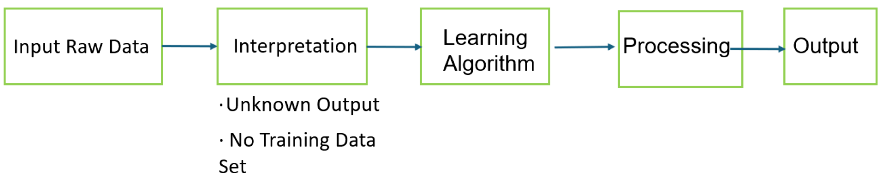

Figure 2. The simple process of unsupervised learning.

2.3. Semi-Supervised Learning

Semi-supervised learning is a hybrid approach that bridges the gap between supervised and unsupervised learning. One of its primary objectives is to optimize the strengths of both paradigms by enabling machines to leverage unlabeled samples for enhanced learning performance. The simplified workflow of Semi-supervised learning is illustrated in **Figure 3**. Semi-supervised learning can be classified into two categories:

- **Transductive learning**: The unlabeled data in the training set includes the specific instances to be predicted.
- **Pure semi-supervised learning**: The training data does not contain the instances targeted for prediction [12].

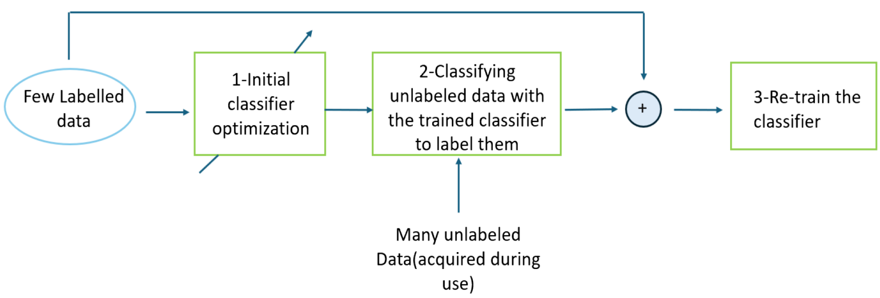

Figure 3. The simple process of semi-supervised learning.

3. Application of Machine Learning in Emergency Management

Using the CNKI (China National Knowledge Infrastructure) database, we collected literature with specific search rules detailed in **Table 1**. The search criteria were set to "machine learning" and "emergency management", resulting in 1472 retrieved articles in both Chinese and English. All literature was uniformly exported in RefWorks format and analyzed through visualization using CiteSpace (version 6.2.6).

Table 1. Literature search rules.

Type	Document attributes
Data source	CNKI Chinese Academic Journals Database
Search query	Topic = Machine Learning * Contingency
Time	December 18, 2024
Time span	October 2003 - December 2024

3.1. Analysis of the Number of Papers Published Annually

Between 2003 and 2024, a total of 1,472 articles were retrieved for analysis. The annual publication trend is illustrated in Figure 4, which reveals an overall upward trajectory in research output. Specifically:

- From 2003 to 2012, the number of publications grew moderately.
- A slight increase occurred in 2014.
- Post-2016, publications surged significantly.

This growth aligns with advancements in machine learning technologies and the rising global prioritization of emergency management, driving heightened scholarly engagement in this interdisciplinary field.

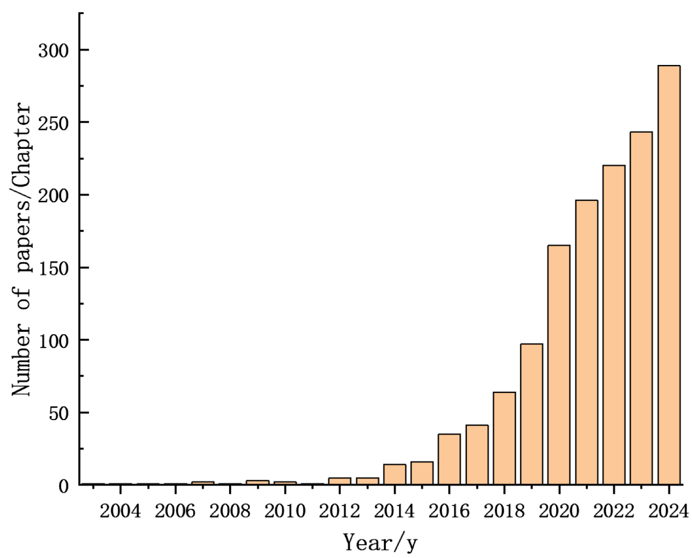

Figure 4. Annual statistics on the number of publications.

3.2. Analysis of the Author of the Post

An analysis of contributing authors among the retrieved literature reveals the top five authors by publication volume, as shown in Table 2. The most prolific author is Ong Marcus Eng Hock, whose research team [13]-[15] predominantly applies machine learning to emergency medicine, focusing on integrating machine learning with medical emergency response systems to improve treatment success rates. The team led by Li Nan [16] developed a novel random forest-based method to screen the most relevant variables contributing to chest pain and constructed a geometric distance-based machine learning scoring system. The results demonstrated that this machine learning-driven variable selection approach exhibits significant potential in identifying key predictors. Their research has laid a foundation for applying machine learning in clinical performance audits and screening critical risk variables, thereby providing strategic direction for advancements in related fields.

Table 2. Top 5 authors in terms of the number of publications.

Serial number	Author	Date of first publication/year	Number of articles
1	Ong Marcus Eng Hock	2012	12
2	Liu Nan	2012	8
3	Schultebraucks Katharina	2020	7
4	Bouzid Zeineb	2020	6
5	Lee Sangil	2019	5

3.3. Analysis of High-Frequency Keyword

Keyword analysis of academic literature identifies research hotspots within a field, enabling the assessment of its developmental trends. By consolidating synonymous terms and analyzing keywords from the retrieved articles, Table 3 lists the top 10 high-frequency keywords, while Figure 5 visualizes their co-occurrence. Key findings include: Machine learning, artificial intelligence (AI), and deep learning dominate as the most frequent keywords in studies on machine learning applications for emergency management.

Table 3. Top 10 high-frequency keywords.

Serial number	Keyword	Frequency
1	Machine learning	50
2	Social media	16
3	Emergency management	10
4	Artificial intelligence	8
5	Deep learning	8
6	Interactive	6
7	Big data	5
8	Data analysis	5
9	Forecast	5
10	Emergency rescue	4

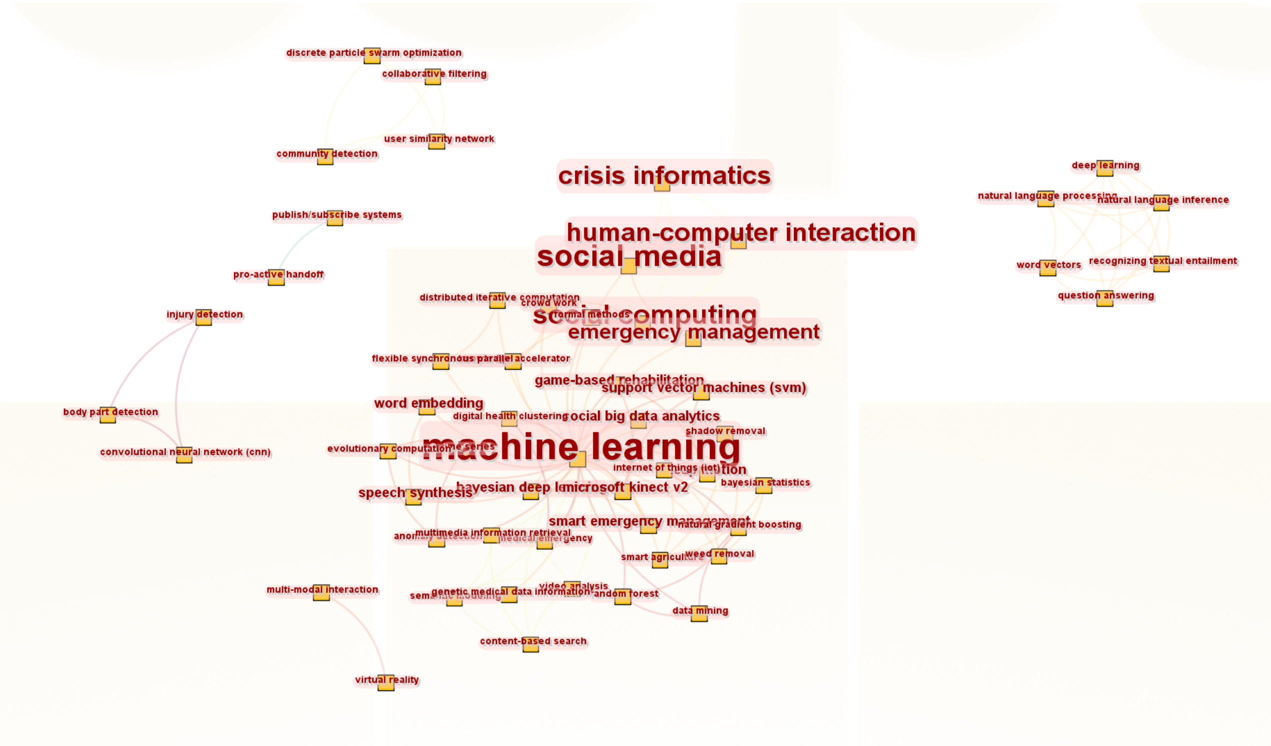

Figure 5. High-frequency keyword.

Advances in technology have facilitated interdisciplinary integration of machine learning, addressing critical challenges such as: forest fire early warning systems [17], liquid nitrogen leakage detection [18], post-disaster resource allocation [19]. Similarly, the application of deep learning in emergency contexts has enabled advancements like: emergency vehicle signal prioritization [20], optimized emergency communication network planning [21], indoor/outdoor evacuation route planning for fire emergencies [22].

3.3.1. Data Analysis

Data Analysis involves selecting appropriate statistical methods to analyze collected massive datasets, uncovering inherent relationships within the data to enhance interpretability and maximize its utility. In the era of big data, it is a purposeful and organized process of collecting, analyzing, and transforming raw data into actionable insights. Data analysis records objective events as identifiable symbols and finds applications across diverse fields. At its core lies the data itself, and modern analysis requires clarifying data variables and understanding their dynamics [23].

A critical application of machine learning in emergency management is data analysis. Disasters and accidents often generate vast amounts of data, including meteorological, geographical, and demographic information. Machine learning processes and analyzes these datasets to identify patterns and trends, providing actionable references for emergency management agencies. For instance, prior to natural disasters, machine learning can analyze historical weather data to forecast future conditions, enabling proactive preparedness.

To mitigate leakage incidents, Zhou Dehong *et al.* [24] conducted a study using multiple LNG (liquefied natural gas) leakage accident reports. They applied Principal Component Analysis (PCA) to the dataset, first extracting the first two principal components to evaluate their classification impact, followed by analyzing the top five components to rank feature weights under each principal component. Subsequently, a Random Forest algorithm was employed to classify the data and assess the contribution of each indicator to classification accuracy. By comparing results from both methods, they systematically identified root causes of leakage.

Addressing challenges in ensuring communication and data security for smart grid control systems, Wang Ning *et al.* [25] proposed a Support Vector Machine (SVM)-based framework integrated with real-time risk assessment and early warning capabilities. By enhancing SVM with Convolutional Neural Networks (CNNs), their system performs risk identification, severity classification, and dynamic alerts while accounting for multifactorial influences. This approach significantly improves the stability and reliability of grid control systems.

3.3.2. Predictive Analytics

Another critical application of machine learning in emergency management is predictive analytics. By learning from and analyzing historical data, machine learning models can forecast potential future disasters or accidents. For example, analyzing historical traffic accident data enables the prediction of high-risk road segments and time periods, empowering transportation authorities to implement targeted interventions and reduce accident probabilities.

Yu Hong *et al.* [26] developed an emergency supplies demand prediction model using machine learning. They employed internal analytical methods to dissect demand management patterns and integrated visual analytics to geotag incident-prone areas, thereby enhancing the model's architecture and improving prediction accuracy for emergency resource allocation.

Liu Fang *et al.* [27] proposed an improved ant colony optimization BP neural network algorithm (IACO-BP) to construct a prediction model for estimating the number of people requiring evacuation during flood disasters.

Liu Jianhua *et al.* [28] applied a BP neural network for urban flood disaster prediction. To enhance accuracy, they combined the BP network with clustering algorithms and introduced "inertia correction" and "S-function output clamping" techniques, achieving effective flood impact forecasting.

3.3.3. Decision Support

Machine learning can also assist emergency management departments in decision-making. In the aftermath of disasters and accidents, emergency management authorities need to make rapid decisions to allocate resources and conduct rescue and relief operations. Machine learning can provide decision support through real-time monitoring and analysis of on-site data. For instance, after an earthquake, machine learning can process image data from affected areas to automatically identify building damage levels, helping emergency management departments prioritize dispatching rescue forces to the most severely impacted regions.

He Peiyu *et al.* [29] proposed a genetic algorithm-based optimization model for emergency material reserve decision-making in transmission line ice-coating disasters. This model uses genetic algorithms to determine effective and rational strategies for emergency material storage during ice-coating events on power lines.

Wei Dong *et al.* [30] developed a novel method based on convolutional neural networks (CNNs) for fault identification and phase selection in transmission line internal/external fault discrimination. Their CNN-based approach simultaneously addresses both issues while resolving the shared weight problem in non-independent classification tasks. This method requires lower sampling rates, eliminates parameter dependencies, and delivers more accurate and reliable results.

Liu Wei *et al.* [31] introduced a deep reinforcement learning-based generator tripping control strategy for power grids. This strategy integrates deep convolutional networks with reinforcement learning, utilizes Q-Learning to compute Q-values, and validates its effectiveness through IEEE-standard verification methods. The control strategy enables autonomous environmental learning and continuous self-adjustment, reducing human error-related accidents while enhancing decision-making accuracy.

4. Challenges Facing Machine Learning in Emergency Management Applications

Current research has demonstrated that supervised learning has been successfully implemented in scenarios such as disaster prediction, and graph convolutional networks (GCNs) have achieved practical application in emergency resource allocation. This marks a critical transition of machine learning from theoretical validation to engineering implementation in the field of emergency management, yet there remains substantial potential for further development. As a critical technology in artificial intelligence, machine learning is continuously evolving. If emergency management fields effectively leverage machine learning techniques, they could play an even greater role in enabling more timely and effective emergency responses.

4.1. Insufficient Training Data

The primary task of machine learning involves training datasets with suitable algorithms, which imposes requirements on data quality. Machine learning applications rely heavily on large volumes of data, yet in emergency management, data quality and completeness are often constrained. After incidents occur, data uploads are frequently delayed, and data quality is difficult to guarantee. To enable machine learning to address emergencies promptly, coordination across departments and advanced equipment is needed to improve data quality and integrity. Additionally, machine learning requires representative datasets to ensure strong model generalization capabilities. However, post-incident data collection often yields chaotic data, necessitating additional steps to filter and organize it. For example, in earthquake disasters, accurately identifying and classifying building damage is critical, but uncertainties in data sources and quality limitations can compromise recognition accuracy [32].

4.2. Interpretability

During machine learning implementation, multiple solutions may exist for the same problem. As model complexity increases, algorithmic interpretability often deteriorates [33]. Machine learning applications typically generate vast amounts of data and predictions, but explaining these results in an understandable and acceptable manner remains challenging. When inputting data, a machine learning model's explanation mechanism provides an interpretation. It is crucial that similar inputs yield consistent or analogous explanations. For research purposes, models must produce interpretable results rather than functioning as "black boxes." Emergency management departments need to understand the internal mechanisms and operational logic of machine learning algorithms and supply sufficient high-quality data to ensure accurate decision-making and resource allocation.

4.3. Security and Privacy Threats

Machine learning involves two key phases—training and prediction—each posing security and privacy risks. In the training phase, privacy threats primarily stem from training data leakage. During prediction, risks include adversarial attacks, privacy breaches, and prediction data leaks [34]. Privacy protection must be prioritized in machine learning applications, focusing on safeguarding sensitive information through processes and rules. When applied to private data, machine learning risks exposing sensitive information, potentially harming affected parties. Privacy protection research in machine learning generally falls into three categories: equivalence class-based methods, data distortion-based methods, and cryptographic methods. In emergency management, large volumes of personal and sensitive data—such as medical records and census data—are involved. Applications must comply with privacy laws, ethical standards, and ensure data security. In the era of big data, where information is critical to productivity and daily life, securing data is paramount. Post-incident data collection must be strictly regulated to prevent leaks and protect personal information.

5. Conclusion

Machine learning, as a critical technology in artificial intelligence, has achieved significant results in emergency management. Given its demonstrated advantages and application value in certain areas of the field, continued research efforts are essential to sustain and build upon these achievements. However, challenges remain in emergency management applications of machine learning, such as the insufficient training data, low interpretability, and security and privacy risks highlighted in this paper. With the rapid advancement of science and technology, machine learning continues to evolve. As these technologies mature and expand in application, they hold great potential to enhance the efficiency and accuracy of emergency response, deliver better rescue and relief services to affected populations, and create greater value for national emergency management development.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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