

Using artificial intelligence methods and models for communication to manage crisis situations^{*}

Serhii Leoshchenko^{1,*†}, Sergey Subbotin^{1,†} and Andrii Oliinyk^{1,†}

¹ National University «Zaporizhzhia Polytechnic», Universytetska St., 64, 69011 Zaporizhzhia, Ukraine

Abstract

The paper examines the problem of improving the efficiency of crisis management by developing an integrated communication method using artificial intelligence. The relevance of the study is due to the growth of heterogeneous data received in real time (sensor systems, social networks, information resources), as well as the need for prompt coordination of actions between Crisis Response subjects in conditions of uncertainty and limited time.

The aim of the work is to create a conceptually and algorithmically based method that combines the analysis of information flows, neural network forecasting of the development of crisis situations and intellectual support for communication between participants in the response system. The proposed approach involves the use of multimodal data and hybrid neural network architectures (in particular models for processing time series, text information and visual data), which allows you to form a generalized situational picture in real time.

A special feature of the study is the focus on the communication component, which is considered not as an auxiliary element, but as a key component of the crisis management system. The method provides automated message processing, classification, prioritization, and adaptive distribution between different categories of users, which helps to increase consistency of actions and reduce response time.

The expected results are the development of an architecture for an intelligent crisis management communication system, formalization of the corresponding method and experimental evaluation of its effectiveness based on real and synthetic data. The practical significance of the study lies in the possibility of applying the proposed approach in civil protection systems, emergency services and information and analytical centers to increase resilience to crisis situations.

Keywords

machine learning, artificial intelligence, neural network, neuromodels, neuroevolution, training, accuracy, communication, crisis situation, forecasting

1. Introduction

In modern conditions of increasing frequency and complexity of crisis situations (natural, man-made, social), the use of artificial intelligence (AI) methods has become one of the key areas of development of risk management systems. Bibliometric studies show a rapid increase in the number of scientific publications in this field, with an average rate of more than 15% per year [1].

Systematic reviews based on the Scopus and Web of Science databases show that AI is actively used at all stages of crisis management:

- forecasting and prevention;
- response;
- recovery [2] [3].

At the same time, researchers emphasize that most existing approaches are fragmented, focused on individual tasks, and not on complex integrated solutions [2].

^{*} CMIS-2026: *Ninth International Workshop on Computer Modeling and Intelligent Systems, May 5, 2025, Zaporizhzhia, Ukraine*

^{1*} Corresponding author.

[†] These authors contributed equally.

✉ sergleo.zntu@gmail.com (S. Leoshchenko); subbotin.csit@gmail.com (S. Subbotin); olejnikaa@gmail.com (A. Oliinyk)

ORCID 0000-0001-5099-5518 (S. Leoshchenko); 0000-0001-5814-8268 (S. Subbotin); 0000-0002-6740-6078 (A. Oliinyk)



Copyright © 2026 for this paper by its authors. Use permitted under Creative Commons License Attribution 4.0 International (CC BY 4.0).

1.1. Forecasting and early detection of crisis situations

One of the most developed areas is the use of machine learning to predict disasters. The most cited works (e.g., Mosavi et al., 2018) demonstrate the high efficiency of ML models in flood prediction problems where ensemble and hybrid methods are used [4].

Modern research also actively uses:

- deep learning for time series analysis;
- neural networks for geospatial data;
- combined models to improve prediction accuracy [5].

In addition, the development of satellite technologies and remote sensing has contributed to the widespread use of convolutional neural networks for damage assessment and identification of risk areas [6].

However, these approaches focus mainly on the physical parameters of the environment, which limits their ability to take into account the social and communication aspects of crises.

1.2. Analysis of information flows and social networks

A significant part of modern research is devoted to the use of social networks as a source of operational information. Classical works (Sakaki et al., 2010; Vieweg et al., 2010) showed for the first time that users can act as “sensors” for crisis events.

Further studies (Imran et al., 2015; Alam et al., 2018) demonstrated the possibility of:

- automatic message classification;
- highlighting relevant information;
- integration of text and Multimedia Data [7].

Modern approaches use transformer models and NLP for:

- analysis of public sentiment;
- identifying requests for help;
- formation of situational awareness [8].

Review papers emphasize that AI analysis of social networks can significantly improve the speed of response and coordination efficiency [9].

At the same time, the key limitation is that most of these systems implement only information analysis, and not communication process management.

1.3. AI in Decision Support Systems

Decision Support Systems (DSS) is an important area of AI development in crisis management.

Modern AI-DSS provide:

- forecasting scenarios for the development of events;
- resource optimization;
- generating recommendations [5].

Research shows that the integration of AI into DSS increases the efficiency of decision-making and allows you to work in conditions of uncertainty [10].

Of particular interest are works with Human-AI collaboration, which demonstrate that combining human experience and AI analytics significantly improves the quality of solutions [11].

However, even in modern DSS, communication between response actors is not a central element of the system, which limits their practical effectiveness.

1.4. Crisis communication and the role of AI

Crisis communications have traditionally been studied in the management and Social Sciences. classical theories (e.g., SCCT) emphasize the importance of:

- timely information;
- reliability;
- consistency of messages.

Current research shows that AI can significantly expand these capabilities by:

- automatic message generation;
- personalization of communication;
- analyzing the audience's reaction;
- information flow management [9].

Especially promising is the direction of AI-enhanced crowdsourcing, which allows integrating information from the population into the response system [12].

However, most studies view communication as a separate component, rather than as the core of a crisis management system.

1.5. Integrated and multimodal AI systems

In recent years, there has been a shift towards creating multimodal systems that integrate:

- text data;
- images and videos;
- touch data;
- social media.

Such systems make it possible to create a complex situational picture and improve the accuracy of analysis [13].

Especially promising is the use of Generative AI, which allows you to:

- model crisis scenarios;
- generate analytical reports;
- support real-time decision-making [13].

At the same time, the researchers emphasize the risks associated with:

- misinformation;
- ethical aspects;
- data security [13].

1.6. Problems and limitations

Despite significant progress, key problems are highlighted in the literature:

- fragmentation of existing solutions;
- lack of integrated architectures;
- low model interpretability;
- limited data quality;
- complexity of integrating different information sources[2][3][9].

The need to create:

- explainable AI;
- multimodal systems;
- adaptive real-time models [2].

1.7. A research gap has been discovered

The analysis of modern research in the field of artificial intelligence for crisis management indicates a high level of development of certain areas, in particular, forecasting emergency events, analyzing data of various nature and supporting decision-making. A significant amount of work is devoted to building models that can process time series, geospatial information, images and text messages, which allows you to form a detailed view of the state of the environment and potential risks. At the same time, research is actively developing aimed at using social networks as a source of operational information, as well as at creating decision support systems that integrate analytical tools to help managers in crisis conditions [14].

At the same time, despite a significant number of scientific results, modern approaches are characterized by fragmentation and focus on solving individual problems without proper integration within a single methodology. In particular, data analysis and forecasting systems

usually function separately from the mechanisms of communication organization, while solutions in the field of crisis communications consider information processes mainly from a managerial or social point of view, without using the full potential of modern AI technologies. As a result, there is a gap between the analytical capabilities of systems and their practical application in real-world conditions, where timely, coordinated and adaptive interaction between different response actors plays a key role.

Special attention should be paid to the fact that in most existing approaches, communication is considered as an auxiliary component of the system, and not as its central element. This approach limits the effectiveness of even high-precision analytical models, since the results of their work are not always transformed into appropriate management actions due to the lack of proper mechanisms for transmitting, interpreting and coordinating information. In addition, the issues of integrating multimodal data in the context of communication processes, as well as adapting information flows to different categories of users in real time, remain insufficiently studied [15].

Thus, the scientific gap lies in the lack of a holistic approach that would combine the capabilities of artificial intelligence for analysis and forecasting with intelligent mechanisms for organizing and optimizing communication between all participants in the crisis response. Filling this gap involves developing an integrated communication method in which information interaction is a key element, rather than a side function of the system.

The analysis of the current state of research in the field of using artificial intelligence for crisis management allows us to state that in recent years there has been significant progress in the development of individual technological components of such systems. The most mature approaches are those related to predicting emergency events, analyzing large amounts of data, and creating Decision Support Systems. The use of deep learning, natural language processing, and multimodal models opens up new opportunities for developing situational awareness and improving the accuracy of risk assessment [14].

At the same time, despite significant achievements, existing solutions do not provide full effective coordination of actions in crisis conditions, which is due to insufficient attention to the organization of communication processes. In most cases, information flows remain poorly structured, and interaction between different response actors is not supported by intelligent tools that can adapt information to the specific context and needs of users. This leads to a loss of time, a decrease in coherence of actions and, as a result, to a decrease in the effectiveness of the response.

In this context, a promising area of further research is the development of integrated approaches in which artificial intelligence is used not only for data analysis, but also for organizing and optimizing communication. This approach involves the creation of systems that can not only form analytical conclusions, but also ensure their timely transmission, interpretation and use by various participants in the crisis management process. A special role is played by the integration of heterogeneous data sources, the use of hybrid neural network models, and the implementation of adaptive mechanisms for managing information flows.

So, further development of research in this area is associated with the transition from isolated AI solutions to integrated communication-oriented systems, which will increase the effectiveness of crisis management and ensure a higher level of sustainability of socio-economic systems to external challenges.

2. Related works

Modern research shows a rapid increase in interest in the use of artificial intelligence in crisis management, especially in the context of analyzing information flows and maintaining communication between response subjects. As the review works show, an interdisciplinary field has been formed in recent years, combining machine learning methods, communication theory, and Decision Support Systems [15]-[20].

One of the key areas is the use of artificial intelligence in crisis communications. In the works of this direction, AI is considered as a tool for processing large amounts of information, automatically generating messages and maintaining interaction with the population. In particular, the study highlights the role of chatbots, text analysis systems, and generative models in ensuring rapid dissemination of information during crisis events [15]-[20].

At the same time, a systematic review shows that most studies focus mainly on detection and classification tasks, while issues of trust, interaction and coordination between subjects remain insufficiently developed. At the same time, the direction of AI in crisis management systems is developing, where the emphasis is shifting to supporting decision-making and forecasting. In these works, artificial intelligence is used to analyze risks, predict events, and optimize resource allocation. Systematic reviews show that such systems combine machine learning, computer vision, IoT, and real-time analytics techniques to improve response efficiency. At the same time, the researchers emphasize the existence of significant limitations related to System Compatibility, Model Interpretation, and ethical aspects of using AI.

A separate group consists of studies devoted to the analysis of information flows during crisis situations. In these works, social networks, sensory data, and service messages are considered as a source of operational information that can be processed using natural language processing and machine learning techniques. Such approaches can increase situational awareness and provide a more accurate understanding of the dynamics of crisis events [15]-[20].

At the same time, a significant part of modern research focuses on the concept of Human-AI collaboration, where artificial intelligence acts not as a substitute for a person, but as a tool for strengthening his cognitive capabilities. This approach highlights aspects such as decision support, resource coordination, situational awareness and staff training.

An important trend is also the transition to the use of generative AI and multimodal models that can simultaneously process text, images, videos, and other types of data. This opens up new opportunities for comprehensive analysis of crisis situations, but at the same time creates risks associated with the spread of disinformation and reduced confidence in automatically generated content.

Despite significant progress, researchers agree that modern systems remain fragmented: they are either focused on data analysis or communication, but rarely combine these components into a single integrated system. In addition, the use of AI in real-world crisis management is still limited due to the complexity of interpreting situations and the need for human control.

A comparative analysis of approaches in the main areas of research is given in Table 1.

Table 1

Main research areas

Direction	Main focus	Technologies	Restrictions
Crisis communications	Dissemination of information	NLP, chatbots, LLM	Lack of attention to coordination
Crisis management	Making decisions	ML, forecasting, IoT	Complexity of integration
Data analysis	Situational awareness	Data mining, CV	Reliability issues
Human-AI interaction	Human support	DSS, explainable AI	Lack of trust
Generative AI	Modeling and generation	GenAI, multimodal	Risk of misinformation

A comparison of AI functionality for crisis management is shown in Table 2.

Analysis of modern scientific publications shows that artificial intelligence is already actively used in crisis management, in particular for data analysis, forecasting and automation of communication. However, most of the existing approaches are highly specialized and do not provide comprehensive coverage of all aspects of crisis management.

Table 2

Comparison of AI functionality

Function	Implementation in research	Level of development
Crisis detection	High (data analysis, sensors)	Mature
Forecast	Average (ML, time series)	Developing
Communication	Medium (chatbots, messages)	Partially implemented
Coordination of services	Low	Insufficiently researched
System integration	Low	Major scientific gap

The essence and comparison of major gaps in existing studies are shown in Table 3.

Table 3

Major scientific gaps

Gaps	Essence
Fragmentation of solutions	Lack of integrated systems
Lack of trust in AI	Transparency and interpretation issues
Limited communication component	Insufficient analysis of interaction between subjects
Ethical risks	Bias, privacy
Poor adaptability	Low ability to work in new scenarios

The direction related to the integration of the analysis of information flows, neural network models and communication processes into a single system focused on coordinating interaction between different response subjects remains particularly insufficiently studied.

This allows us to conclude that there is a scientific gap, which consists in the absence of a holistic communication method of crisis management based on artificial intelligence, combining analytical, predictive and communication functions within a single architecture.

3. Materials and methods

The communication method using artificial intelligence for crisis management is an integrated system for organizing information interaction that combines modern digital technologies, analytical algorithms and management procedures. Its essence is to ensure a continuous cycle of working with information: from its collection to the formation of management decisions: in order to increase the effectiveness of responding to crisis events. This approach can significantly reduce the processing time of large amounts of heterogeneous data and reduce the level of uncertainty, which is critical in dynamic and unpredictable situations.

Within this method, the ability of artificial intelligence to integrate information from a variety of sources, including technical monitoring systems, information resources of organizations,

communications of response services and messages from open sources, in particular social networks, plays a key role. The received data is processed automatically, including cleaning, structuring, and verifying its validity. This creates the basis for the formation of a single information space in which all participants in the crisis management process can work with consistent and up-to-date information.

The next stage involves an intelligent analysis of the situation, during which artificial intelligence algorithms classify crisis events, assess their scale, identify potential risks and predict possible development scenarios. Through the use of machine learning models and neural networks, it becomes possible not only to respond to the current state of the system, but also to anticipate future changes, which allows you to move from reactive to proactive crisis management.

An important component of the method is to maintain communication between all stakeholders. Artificial intelligence helps optimize information flows by automatically generating messages according to context, priority, and target audience. This ensures consistency between different services, reduces information overload, and increases the speed of mission-critical data transfer. In addition, the use of intelligent systems allows you to adapt messages to different communication channels and ensure effective interaction with the population.

Based on a comprehensive data analysis, the system generates recommendations for making managerial decisions, suggesting possible response scenarios and optimal resource allocation options. At the same time, the final decision remains with the person, but artificial intelligence acts as a support tool, which significantly increases the validity and efficiency of management actions.

The final element of the method is the feedback mechanism, which ensures the accumulation of experience and improvement of the system. After the crisis situation is completed, the effectiveness of decisions and actions taken is analyzed, which allows you to adjust models, improve the accuracy of forecasting, and adapt the system to new conditions. Thus, the communication method using artificial intelligence acquires the properties of a self-learning system that can evolve along with the growing complexity of crisis challenges.

3.1. Input data

Training samples for the communication method of crisis management using artificial intelligence are comprehensively formed data sets that reflect both the crisis events themselves and the information processes that accompany them. They serve as a basis for training models that can analyze the situation, interpret information flows, and maintain effective interaction between all response participants. A special feature of such samples is their multidimensional nature and heterogeneity, since they combine structured, semi-structured and unstructured data.

An important part of the training samples is historical data on crisis situations, which includes information about the type of event, its temporal and spatial characteristics, the course of development and consequences. Such data allow the model to identify patterns in the occurrence and escalation of crises, as well as form a basis for predicting similar scenarios in the future. At the same time, data on management decisions made during the response process are equally important, since they allow us to evaluate the effectiveness of various strategies and teach the system to offer optimal options for action.

A separate layer consists of communication data that reflects information exchange between services, management bodies and the population. This can include text messages, conversation records, reports, and data from social networks. Such samples are usually annotated by content, urgency, and reliability, which allows the model to learn how to recognize critical information, filter noise, and generate relevant messages for different audiences.

Equally important are sensor and observation data coming from technical monitoring tools, such as sensors, cameras, drones, or satellites. They provide an objective display of the physical state of the environment and allow the system to automatically detect signs of danger or changes in the development of events. Combining such data with communication flows creates a more complete picture of the situation and improves the accuracy of analytical models.

Given the limited real-world data on crisis situations, synthetic or simulated samples also play an important role. They are formed using simulation models and scenario analysis and allow you to reproduce rare but critical events. This makes it possible to prepare the system for various scenarios and increase its resistance to uncertainty.

Thus, the training samples for such a method are a complex integrated data system that encompasses both actual crisis response experiences and simulated scenarios, providing comprehensive training of artificial intelligence models to effectively support communication and decision-making in critical environments.

3.2. Choosing the type of analytic model

Neural network topologies used in communication methods of crisis management form a multi-level intelligent basis for a system capable of working with heterogeneous and dynamic data flows. Since crisis situations are characterized by high uncertainty, rapid changes in conditions, and the need to process large amounts of information from various sources, no single type of neural network is sufficient. Therefore, in practice, complex approaches are used that combine several topologies, each of which is focused on a specific data type or analytical task.

Recurrent neural networks, in particular LSTM and GRU architectures, are effectively used to analyze the temporal dynamics of crisis processes and message flows. They allow you to take into account the relationships between events over time, which is critical for predicting the development of the situation, identifying escalations and assessing the consequences of management decisions. Such models work well in sequential data processing tasks, such as dispatching logs or message streams from response services.

Convolutional neural networks are used to process visual and spatial information, which can effectively analyze images and videos from surveillance cameras, drones, or satellites. They provide automatic detection of signs of emergency situations, assessment of the scale of damage and localization of dangerous areas. This significantly increases the speed of the initial assessment of the situation without the need for completely manual data analysis.

An important role in modern systems is played by transformer architectures that specialize in processing large amounts of text information. In times of crisis, these can be messages from social networks, citizens, appeals, or internal communications between services. Such models can not only classify and generalize text, but also generate relevant messages, which allows you to automate part of the communication process and reduce the information load on operators.

Since the interaction between response participants is of a network nature, it is advisable to use graph neural networks that model the structure of connections between different subjects and infrastructure objects. They allow you to analyze information transmission routes, identify critical communication nodes, and optimize coordination between services. This is especially important in the context of complex multi-level control systems.

Additionally, autoencoders and other unsupervised models are used, which provide detection of anomalies in data and allow you to filter out noise or false information. This contributes to the early detection of potential threats and increases the reliability of the system's functioning in conditions of information overload.

Summarizing, it can be noted that the effective implementation of the communication method of crisis management is based on the integration of various neural network topologies within a single hybrid architecture. This architecture allows you to simultaneously take into account the temporal, spatial, semantic and network aspects of crisis processes, providing a comprehensive analysis of the situation and support for real-time decision-making.

Table 4 is a generalizing table that systematizes neural network topologies in the context of the communication method of crisis management

Table 4
Major scientific gaps

Neural network type	Main data type	Key tasks	Advantages	Restrictions
Recurrent (LSTM, GRU)	Time series, text streams	Forecastin the development of events, analyzing message sequences	Accounting for time dependencies, working with dynamics	Learning complexity, limited parallelization
Convolutional (CNN)	Images, videos, and spatial data	Object detection, damage analysis, territory monitoring	High accuracy in visual tasks	They don't work well with time dependencies without extensions
Transformer-models	Text, large information flows	Classification, generalization, and message generation	Scalability, efficiency in big data	High computing costs
Graph neural networks (GNNS)	Network structures (relationships between objects)	Communication analysis, interaction optimization	Taking into account the structure of relationships	Complexity of graph construction and training
Autoencoders	Any (usually multidimensional)	Anomaly detection, data compression	Working without marked-up data	Limited interpretability
Hybrid models	Combined (text + video + time)	Comprehensive analysis of crisis situations	Versatile, high efficiency	High implementation complexity

3.3. Designing the system architecture

The architecture of the neural network system for implementing the communication method of crisis management is formed as a multi-level integrated structure capable of working with heterogeneous data flows and ensuring their coordinated use to support decision-making. At its core, such a system combines the processes of collecting, processing, analyzing, interpreting and transmitting information coming from a large number of sources, including sensor networks, information systems of organizations, communications of response services and public messages. Architecturally, this means building a single information space in which all data is reduced to a consistent format, synchronized over time, and made available for further intellectual analysis.

At the initial stage of the system's operation, data is continuously collected from distributed sources that characterize the state of the environment and the course of potentially crisis processes. Since this data is of a different nature – from numerical indicators and sensor signals to text messages and video streams-the preprocessing subsystem plays an important role. It provides cleaning of information from noise, elimination of omissions, normalization of parameters and transformation of data into a format suitable for further machine analysis. It is at this stage that the initial identification of features occurs, which significantly affects the efficiency of the entire system, and early detection of anomalies that signal the possible development of a crisis situation can also be implemented.

The key element of the architecture is the level of specialized neural network models, organized on the principle of parallel processing of various types of data. To analyze the temporal dynamics of processes, recurrent neural networks are used, which allow identifying patterns of events, assessing the risks of their escalation, and forming short- and medium-term forecasts. Processing of visual information, in particular videos and images, is carried out using convolutional neural networks that can automatically identify objects, determine the extent of damage and localize danger zones. Text streams coming from social networks, service communication channels, or citizens' appeals are analyzed by models based on the transformer architecture, which provide a deep understanding of the content of messages, their classification and generalization. At the same time, graph neural networks are used to study the structure of interaction between various system participants: control bodies, response services, and infrastructure objects, which allow modeling complex communication connections and identifying critical elements of the system.

The results of individual neural network modules are not used in isolation, but are integrated in a single Analytical Space. At the integration level, heterogeneous estimates and forecasts obtained from different models are combined to form a generalized idea of the current state of the system and possible scenarios for the development of events. This approach reduces uncertainty, increases the reliability of estimates, and provides more informed decision support. To implement this function, ensemble methods, metamodels, or probabilistic approaches can be used that coordinate the results of different sources of analysis.

At the next level of the architecture, a decision support subsystem is implemented, which turns the results of the analysis into specific recommendations for management entities. It creates possible response scenarios, evaluates their effectiveness based on current constraints and resources, and ranks alternatives based on specified criteria. In this context, it is important to use Adaptive Methods, in particular reinforcement learning or neuroevolution approaches [21], which allow the system to gradually improve its recommendations based on accumulated experience.

A separate place in the architecture is occupied by the communication level, which provides direct interaction between all participants in the crisis response process. It is here that analytical results are transformed into clear and timely messages received by management bodies, operational services and the population. Intelligent mechanisms at this level allow you to automatically generate messages based on the context, prioritize them, adapt the content to the target audience, and provide effective feedback. Thus, the communication layer acts not only as a channel for transmitting information, but also as an active element for controlling information flows.

The final component of the architecture is the level of training and adaptation that ensures the long-term effectiveness of the system. After each crisis situation, new data is accumulated, the results of decisions made are analyzed, and models are updated. This allows the system to gradually adapt to new conditions, take into account the changing nature of threats, and improve the accuracy of forecasts. In fact, the system acquires self-learning properties, which is crucial in an environment with high uncertainty and dynamics.

Summarizing, it can be argued that such an architecture is a complex cyberphysical system that combines multimodal data processing, distributed intelligence and adaptive communication. Its effectiveness is determined by the ability to integrate different types of Information, respond quickly to changes in the situation, and ensure coordinated interaction between all participants in the crisis management process. It is this integration of neural network approaches and communication mechanisms that creates the basis for building modern Decision Support Systems in critical conditions.

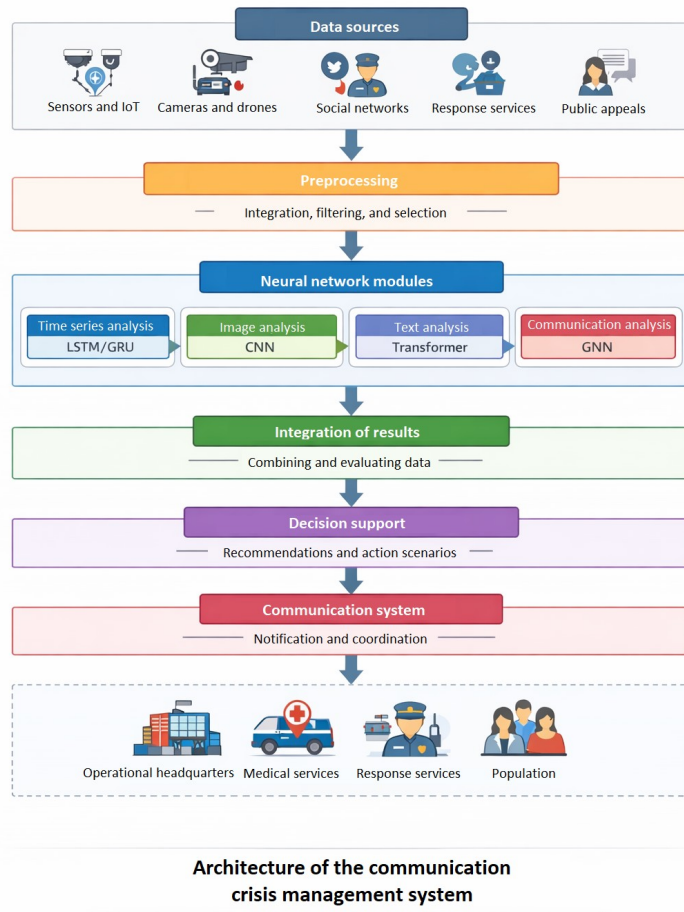


Figure 1: Architecture of the communication crisis management system

3.4. Methodology

In this paper, we will focus on implementing AI specifically at the analytics base stage to identify, classify, and analyze disaster-related tweets generated before, during, and after a hurricane. The main goal is to collect all useful information that can be related to the development of natural disasters, including the stages of preparedness, response and recovery.

Considering the step-by-step approach, it should be noted that data collection, sampling development, and procedures are first performed to collect and divide the entire dataset into training and testing parts. Next, the model is trained on the basis of the LSTM network with classification on pre-prepared training and test kits to evaluate various classification methods.

The second stage involves binary classification of disaster-related tweets using LSTM and classification of detailed information by multiple labels. Therefore, an experiment is first conducted to test the effectiveness of logistic regression, linear SVM, Ridge, CNN, and LSTM classification methods in binary classification of disaster-related information. Using the non-revolutionary synthesis of the LSTM model, the model with the best indicators of the conceptual correspondence of the LSTM to the sequential order of text data is selected from several solutions, and then the selected model is used to classify the rest of the data set into related and unrelated tweets. Taking into account the structural features of the LSTM, detailed information about the categories of tweets related to natural disasters, such as affected individuals, tips and warnings, and charity and support, is extracted from the context of posts, using an approach to modeling the topic without control.

Another important step is to use spatial adaptive core smoothing and density-based spatial clustering to determine the relative significance and impact areas for each Information category, respectively, as in [22]. This is important in light of further test comparisons of the spatial and temporal characteristics of categorized tweets with data on dramatic weather changes to pinpoint potential areas for emergency response and recovery, as well as to identify geographical differences in social media usage during natural disasters.

4. Experiments and results

Using a vectorized representation of a manually marked dataset, a series of binary classifiers were trained. The training sample intentionally included both relevant and irrelevant data previously classified by experts, which made it possible to improve the accuracy of models in recognizing irrelevant messages. The original dataset contained 20,413 tweets, of which 7,801 were classified as relevant and 12,612 as irrelevant.

To ensure balance during training, a sub-selection procedure was applied: a subset was formed with the same number of examples of both classes: 7801 relevant and 7801 irrelevant tweets. The obtained data were divided into training and test samples in the ratio of 80% to 20%. As a result, 12,481 sequences were used for training, and 3,121 were used for testing. based on the training sample, various models were independently trained, in particular logistic regression, SVM, CNN, and LSTM, described in the methodology, with variable parameters. A test sample was used to check the quality of each model. The parameters were adjusted in such a way as to avoid retraining and achieve maximum accuracy during validation.

Table 5 shows the results of evaluating models that demonstrate that LSTM-type neural networks and CNN-based models are significantly superior to traditional machine learning algorithms. The accuracy score is defined as the proportion of correctly classified positive and negative examples from the total number of tweets. The generalizing metric F1 takes into account both precision and recall according to the formula:

$$F1\ score = 2 \cdot \frac{precision \cdot recall}{precision + recall}, \quad (1)$$

where *precision* is the fraction of relevant tweets among all relevant tweets (i.e. *true positives / true positives + false positives*);

recall is the fraction of relevant tweets over the total amount of tweets (i.e. *true positives / true positives + false negatives*);

Table 5

Accuracy, precision, recall and F1 scores for proposed classifier models based on RNN (LSTM) and CNN

	LSTM	GRU	CNN	DNN	SVM
Accuracy	0,9808	0,6313	0,87	0,86408	0,5148
Precision	0,9983	0,632	0,87074	0,86482	0,5099
Recall	0,971	0,6377	0,87148	0,86556	0,5266
F1 Score	0,993	0,6306	0,87222	0,8663	0,5098

The results obtained demonstrate a significant difference in the efficiency of different models for the binary classification problem. The highest accuracy values (accuracy = 0.9808) are observed in the LSTM model, which indicates its ability to effectively take into account the consistent nature of

text data and long-term relationships between words. This is also confirmed by very high values of precision (0.9983), recall (0.971) and F1-score (0.993), which indicates a balanced and stable operation of the model without a significant skew between false-positive and false-negative results. The CNN model also shows high results (accuracy = 0.87), inferior to LSTM, but significantly superior to classical methods. Its precision (0.87074), recall (0.87148), and F1-score (0.87222) scores are well balanced, indicating effective extraction of local features from the text, although without deep consideration of the long-term context. DNN shows a similar level of efficiency (accuracy = 0.86408), but is slightly inferior to CNN in all metrics. This may be due to a lower ability to process structured sequences without specialized mechanisms, such as convolutions or recurrent bonds. The GRU model shows noticeably lower accuracy (accuracy = 0.6313) compared to LSTM, although architecturally they are similar. This is probably due to fewer parameters and a simplified GRU structure, which in this case was not enough to fully capture complex dependencies in the data. The worst results are shown by SVM (accuracy = 0.5148), whose value is close to random guessing for binary classification. Low precision (0.5099), recall (0.5266), and F1-score (0.5098) indicators indicate that traditional machine learning methods are significantly inferior to neural network approaches in text flow analysis tasks. Overall, the results support the superiority of deep neural networks, especially recurrent ones (LSTMs), in natural language processing tasks where it is important to take into account the context and consistency of data.

5. Conclusion

The obtained high values of classification accuracy indicate that modern artificial intelligence models are able to efficiently process large amounts of information and identify relevant messages in data streams in a mode close to real time. This is critical for Threat Management, where the speed of response and the quality of Information Analysis directly affect decision-making. Using such models allows you to automate the initial processing of messages from social networks, response services, and other sources, reducing the burden on operators and increasing the overall efficiency of the response system.

In addition, the introduction of neural network approaches provides a more flexible and adaptive threat management system that can take into account complex contextual dependencies and quickly adapt to changes in the information environment. This opens up opportunities for creating intelligent decision support systems that not only analyze the situation, but also offer options for action based on previous experience and accumulated data. As a result, the accuracy of predicting the development of crisis situations increases and the risk of errors related to the human factor decreases.

Further prospects for the development of such approaches are associated with the integration of various types of data (text, geospatial, sensor), the use of more complex deep learning architectures, and the introduction of mechanisms for explicable artificial intelligence. This will not only improve the accuracy and reliability of models, but also make their solutions transparent and understandable for specialists. In the long term, such systems can become the basis for fully automated crisis management platforms that can provide proactive threat detection and coordination between different services in conditions of uncertainty.

Acknowledgements

The work was carried out with the support of the state budget research projects of the state budget of the National University "Zaporozhzhia Polytechnic" "Intelligent information processing methods and tools for decision-making in the military and civilian industries" (state registration number 0124U000250) and "Artificial intelligence tools for control and management of technical and social systems under martial law" (state registration number 0125U000854).

Declaration on Generative AI

For generated some icons for fig. 1 the authors used ChatGPT Images 2.0.

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

References

- [1] Wibowo, A., Santoso, H., & Nugroho, R. (2025). Bibliometric review of AI in disaster management. *Journal of Applied and Basic Sciences*, <https://jamba.org.za/index.php/jamba/article/view/1776/3380>
- [2] Cheong, C., Lim, S., & Tan, J. (2025). Systematic review of AI in disaster management. *Human Resource Management Academic Research*, <https://hrmars.com/ijarbss/article/view/26436/Enhancing-Disaster-Management-through-Artificial-Intelligence-A-Systematic-Review>
- [3] Abid, M., Khan, S., & Ali, R. (2021). Integrated AI disaster management approach. *Bohrium Digital Publications*, <https://bohrium.dp.tech/paper/arxiv/e120256381360d7d62e225cc54db27f21e04d43d33de140209af72ca68aeaa0>
- [4] Mosavi, A., Ozturk, P., & Chau, K. W. (2018). Flood prediction using machine learning: A review. *Journal of Hydrology*, <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC12067534/>
- [5] Drakaki, E., Karypidis, S., & Petrakis, E. (2022). Machine learning in disaster management. *Springer Lecture Notes in Computer Science*, https://link.springer.com/chapter/10.1007/978-3-031-82377-0_16
- [6] Al Shafian, S., & Hu, Y. (2024). Remote sensing and ML in disaster management. *iManager Publications*, <https://www.imanagerpublications.com/article/21675>
- [7] Alam, F., Imran, M., & Ahmad, N. (2018). Social media analysis in disasters. arXiv preprint, <https://arxiv.org/abs/1805.05144>
- [8] Imran, M., Castillo, C., & Diaz, F. (2022). AI for disaster response via microblogs. *IJCAI Proceedings*, <https://www.ijcai.org/proceedings/2023/0701.pdf>
- [9] Abid, M., Khan, S., & Ali, R. (2025). AI-enhanced crowdsourcing for disaster management. *International Journal of Emergency Medicine*, <https://intjem.biomedcentral.com/articles/10.1186/s12245-025-01009-9>
- [10] Chen, H., Li, P., & Zhang, W. (2024). AI DSS in disaster management. *International Journal of Research and Publications*, <https://ijrpr.com/uploads/V6ISSUE4/IJRPR42210.pdf>
- [11] Domfeh, E., & Dancy, M. (2025). Human-AI collaboration in decision making. arXiv preprint, <https://arxiv.org/abs/2509.12034>
- [12] Abid, M., Khan, S., & Ali, R. (2025). Social media and AI integration for emergency management. *International Journal of Emergency Medicine*, <https://intjem.biomedcentral.com/articles/10.1186/s12245-025-01009-9>
- [13] Raj, A., Singh, V., & Kumar, P. (2025). Generative AI in disaster management. arXiv preprint, <https://arxiv.org/abs/2505.08202>
- [14] Gupta, S., Verma, R., & Sharma, K. (2023). Scientometric analysis of AI disaster research. *Springer Lecture Notes in Computer Science*, https://link.springer.com/chapter/10.1007/978-3-031-82377-0_16
- [15] Jiang, L., Chen, J., & Zhang, Q. (2022). AI in geohazard research. *Springer Lecture Notes in Computer Science*, https://link.springer.com/chapter/10.1007/978-3-031-82377-0_16
- [16] Lin, Y., Wang, H., & Li, S. (2021). Deep learning for earthquake early warning. *Springer Lecture Notes in Computer Science*, https://link.springer.com/chapter/10.1007/978-3-031-82377-0_16

- [17] Kappi, R., & Mallikarjuna, P. (2024). Highly cited AI disaster papers: A bibliometric study. *International Journal of Research and Publications*, <https://ijrpr.com/uploads/V6ISSUE4/IJRPR42210.pdf>
- [18] Yigitcanlar, T., Kamruzzaman, M., & Ioppolo, G. (2021). AI in smart cities and disasters. *Science of The Total Environment*, <https://www.sciencedirect.com/science/article/pii/S0736585321001684>
- [19] Ibrahim, R., & Mishra, S. (2021). AI for disaster resilience. *Pakistan Journal of Life and Social Sciences*, https://pjlss.edu.pk/pdf_files/2025_2/128-139.pdf
- [20] Kankanamge, N., Li, P., & Perera, C. (2020). Disaster management frameworks and AI. *Science of The Total Environment*, <https://www.sciencedirect.com/science/article/pii/S0736585321001684>
- [21] S. D. Leoshchenko, A. O. Oliinyk, S. A. Subbotin, V. A. Lytvyn, V. V. Shkarupylo. Modification and Parallelization of Genetic Algorithm for Synthesis of Artificial Neural Networks. *Radio Electronics, Computer Science, Control*, 2019, No. 4, pp. 87–97. DOI: 10.15588/1607-3274-2019-4-7 . URL: <https://ric.zp.edu.ua/article/view/193117>
- [22] Muhammed A. Sit, Caglar Koylu, Ibrahim Demir. *Identifying Disaster-Related Tweets and Their Semantic, Spatial and Temporal Context Using Deep Learning, Natural Language Processing and Spatial Analysis: A Case Study of Hurricane Irma*. *International Journal of Digital Earth*, 2019, Vol. 12, No. 11, pp. 1205–1229. DOI: 10.1080/17538947.2018.1563219. URL: <https://www.tandfonline.com/doi/full/10.1080/17538947.2018.1563219>