https://doi.org/10.31449/inf.v49i36.10578 Informatica **49** (2025) 253–268

Dynamic Crisis Propagation Modeling and Emergency Scheduling via a Grasshopper-Optimized Spatiotemporal Graph Neural Network

Tingting Wang
School of Tourism and Public Administration, Zhuhai College of Science Technology, Zhuhai 519000, Guangdong, China
E-mail: Wangtingting688@hotmail.com

Keywords: public crisis propagation, emergency resource scheduling, dynamic grasshopper optimized spatiotemporal graph neural network (DGO-ST-GNN), crisis modeling

Received: August 5, 2025

Public crises such as natural disasters, pandemics, and large-scale industrial accidents require intelligent real-time decision-support systems capable of accurately predicting crisis severity and optimizing emergency resource allocation. This research introduces a Dynamic Grasshopper-Optimized Spatiotemporal Graph Neural Network (DGO-ST-GNN) designed to model crisis propagation by integrating spatial and temporal dependencies in crisis evolution. The architecture consists of stacked Spatiotemporal Graph Convolution Blocks, combining graph convolution layers for spatial region relationships and gated recurrent temporal units for sequential progression of crisis patterns. To enhance convergence stability, generalization, and performance consistency, a Dynamic Grasshopper Optimization Algorithm (DGOA) adaptively tunes hyperparameters, including learning rate, batch size, convolution depth, and dropout rate at the end of each training epoch. The model is trained on 1,030 manually annotated geo-tagged crisis-related tweets containing crisis type, sentiment polarity, severity level, resource availability, timestamp, and geolocation. Text preprocessing includes tokenization, stop-word removal, and Word2Vec embeddings (300-dimensional), which are used to construct semantic similarity edges for graph generation across urban regions. Data are partitioned using an 80:20 train-validation-test split, and implementation is performed in Python. Experimental evaluation compares DGO-ST-GNN with traditional machine learning models (SVM, Logistic Regression, Random Forest, Naïve Bayes) and deep-learning baselines (CNN, LSTM, CNN-LSTM, BERT, XLNet). The proposed shows superior classification performance for crisis severity prediction,97% accuracy, 95% precision, 96% recall, and 94.9% F1-score, outperforming the strongest baseline Although DGOA increases per-epoch runtime by 38.7%, the improvement significantly strengthens predictive robustness and scalability for real-time emergency response.

Povzetek: Predlagani model združi prostorsko-časovne povezave in optimizacijo hiperparametrov, da iz podatkov (npr. objav na družbenih omrežjih) z visoko natančnostjo napove resnost kriz ter podpre hitrejše odločanje in razporejanje virov.

1 Introduction

Natural disasters, pandemics, industrial accidents, and significant system breakdowns are types of public crises that have come to characterize modern society [1]. As a result of an increase in factors such as population density and urbanization, and a shift in climate, the frequency and intensity of disasters are on the rise [2]. These crises, in addition to the destruction of property and disturbing the ecosystem in the affected areas, also have long-lasting psychological and economic effects. Crowded urban areas, where infrastructure is highly interconnected, are especially vulnerable to small-scale interruptions that can spiral out of control and escalate into significant emergencies [3]. Such catastrophes require a swift and effective response. The first few hours after a crisis are often the most critical; despite being the most fragile, initial choices during that phase heavily influence the outcome of rescue and relief efforts [4]. Coordinated action and allocation of resources, real-time situation monitoring, and command over the environment call for up-to-the-minute crisis response capabilities. The unpredictability of crises, the rapid pace of change, and the limitations of current information technologies render it impossible to achieve such adaptability [5].

The rise of social media platforms and other digital channels has transformed the approach to crisis handling. People use the internet to update and share their observations and needs. During emergencies, a stream of location-specific, real-time information is generated [6]. This digital trace may allow for better and more community-informed governance and enable more responsive community-informed decision-making [7]. However, dealing with a multitude of unstructured data for operational workflow integration is challenging, particularly for operational frameworks that focus on data credibility, noise, and systematic change identification [8]. There is a growing need for intelligent systems capable of monitoring the development of public crises, andthat can also provide strategic insights for time-critical, complex data in real time [9]. Effective prioritizing of response efforts should be made possible by such systems, which should also be able to identify crucial regions and capture spatial and temporal connections [10]. The creation of data-driven, responsive, and scalable crisis management systems has become crucial for legislators, first responders, and software developers alike as metropolitan areas continue to expand and climate-driven disasters become more prevalent [11]. The main difficulty is precisely simulating how crises spread, which is dynamic, intricate, and linked, particularly in urban settings. Traditional systems hinder effective and efficient responses to quickly changing public emergencies due to their inability to integrate unstructured input from social media, make decisions in real-time, and schedule resources adaptively under uncertainty.

The proposed research seeks to improve real-time crisis response by precisely simulating the spread of public disasters and improving resource allocation. It presents a DGO-ST-GNN that employs an adaptive scheduling algorithm to evaluate rescue efforts according to severity, urgency, and resource limitations, and tracks the evolution of crises using geotagged social media data.

Key contributions

- The system uses geotagged tweets as a crowdsourced, real-time data source for crisis monitoring. By performing this, impacted areas and evolving conditions are instantly detected.
- A strong preprocessing technique is used, involving stop-word removal and tokenization to enhance feature extraction. This ensures that important features can be recovered for accurate graph formation and improves the quality of the data.
- For crisis-related text data, semantic features were extracted using Word2Vec to capture contextual meanings of words in social media posts. This enriched each graph node with relevant linguistic information to improve crisis propagation modeling.
- The suggested DGO-ST-GNN extracts patterns of changing crises. It increases prediction accuracy in a dynamic environment and improves semantic representation.

Objective of the research: To develop a robust framework for real-time crisis severity classification and optimized emergency resource scheduling using geo-tagged social media data. Specifically, the study aims to improve classification performance of crisis events using a DGO-ST-GNNreduce scheduling latency in resource allocation by integrating predictive crisis modelling with adaptive optimization; and enhance the model's adaptability to dynamic inputs and evolving crisis scenarios through spatiotemporal feature extraction and hyperparameter tuning. These objectives collectively ensure timely and accurate decision-making for effective emergency response.

RQ1: *How effectively can a Dynamic Grasshopper-Optimized Spatiotemporal Graph Neural Network (DGO-ST-GNN) model spatiotemporal crisis propagation be using geo-tagged social media data, compared to existing machine-learning and deep-learning approaches?*

RQ2: *To what extent can the DGO-ST-GNN-based multitask rescue scheduling algorithm improve real-time emergency resource allocation efficiency—specifically reducing mean and maximum wait times—compared to traditional scheduling strategies such as FCFS, Priority Scheduling, and Hybrid Multitask Scheduling?*

2 Related work

Existing models for crisis transmission and emergency resource allocation frequently struggle with dynamic, real-time data and complicated spatial-temporal connections. Recent advances in deep learning and graph neural networks provide potential solutions, but they are still limited in adaptability and efficiency throughout large-scale public emergencies.

Using wireless sensor-based positioning to improve emergency public resource scheduling was the objective of the research [12]. With natural number coding and a penalty mechanism, it presents an enhanced MultiAgent Genetic Algorithm Multi-Target Emergency Resource Scheduling (MAGA-MTERS). The technique was more cost-effective and efficient than conventional genetic algorithms. Improved sensor accuracy helps with scheduling the results. Potential scalability and the complexity of real-world deployment were drawbacks.

Deep reinforcement learning was employed in the experiment [13] to optimize the scheduling of urban emergency resources during public health emergencies. The Deep Q Network created a distribution system for effective scheduling of routes. Improved scheduling efficiency was demonstrated via simulation results. However, a major drawback was that deep learning models require plenty of central processing unit (CPU) resources, which makes them computationally expensive.

Employing effective logistics scheduling to reduce rescue times during storm surge events was the aim of the evaluation [14]. It employed Deep Deterministic Policy Gradient (DDPG) and Mixed-Integer Linear Programming (MILP) techniques. The results indicated that while DDPG was significantly faster and had a somewhat lower accuracy, MILP provided the best results, but it took a long time. Scalability for MILP and decreased accuracy in DDPG for complicated scenarios were among the limitations.

Research [15] seeks to enhance real-time crisis event recognition from noisy short-text data on social media platforms. It suggests SatCoBiLSTM, a hybrid deep learning model that combines multi-scale CNN, BiLSTM, and self-attention to extract hierarchical features. It earned a 96% F1-score after being tested on three real-world datasets. While successful, its drawbacks include a possible reliance on labeled data and a significant computing burden.

Enhanced spectrum efficiency in unmanned aerial vehicle (UAV)-assisted emergency communication for B5G/6G networks was the aim of the research [16]. Used a convolutional neural network (CNN) and Q-learning, it suggested a deep reinforcement learning (DRL)-based resource allocation technique that simultaneously optimizes user scheduling, UAV zone selection, and macro base station power. The efficiency gains over current methods were demonstrated by the results. Reliance on antiquated channel information in time-delay systems and oversimplified scheduling assumptions were among the drawbacks.

By employing AI to identify urgent help requests on Twitter, the research [17] seeks to assist first responders during emergencies. It selects tweets related to Hurricane Harvey, classifies them according to urgency and relevance, and evaluates machine learning models. CNN and conventional models perform worse than Bidirectional Encoder Representations from Transformers (BERT) and Extra Long Network (XLNet). Despite its effectiveness, it only used one disaster dataset, which limits its generalizability.

Research [18] used UAVs as mobile edge computing nodes to improve emergency edge computing in 5G networks. It presented a decentralized task offloading and resource allocation mechanism called collaborative computation offloading and resource allocation-DRL (CCORA-DRL), which was based on DRL. To minimize energy and latency, UAV agents employed a deep deterministic policy gradient. Results surpassed those of A3C models. However, real-time network uncertainties and UAV mobility might impact the system's performance.

By using a deep learning algorithm in the analysis of media framing, the experiment [19] seeks to maximize crisis communication. A hierarchical transformer design was suggested to identify changing narrative structures throughout crises. The accuracy of the model was 91.2%, surpassing baselines. The findings indicated that frame changes impact public opinion and confidence. Cultural prejudice, the omission of visual framing, and the high computational requirements were some of the limitations.

The use of a convolutional neural network- long short-term memory (CNN-LSTM) model to predict public opinion crises and minimize harmful information on social networks was the objective of the research [20]. It uses deep learning for text classification, gathers IoT-based user data, and achieves an accuracy of 92.19%. The model outperforms GAN, CNN, LSTM, recurrent neural network (RNN), and Transformers. One drawback was that it requires huge, high-quality datasets to function at its best.

The use of an IoT-based Adam-optimized LSTM model to forecast the evolution of Online Public Sentiment (OPS) amid public situations was the aim of the research [21]. It simulated OPS dynamics using AI and big data. The accuracy was higher than with standard models (MRE: 0.06) in the results. Real-time adaptability and wider generalization across various emergency events and differing network behaviors were its limitations.

Improved real-time identification of catastrophic occurrences by merging picture and text data from social media was the aim of the research [22]. It presents a multimodal middle fusion model that employs cross-modal and self-attention techniques. On CrisisMMD tasks, it achieves up to 91.53% accuracy, outperforming early/late fusion and unimodal techniques by 2-5%. One restriction is the reliance on high-quality, synchronized multimodal data.

The purpose of the experiment [23] was to use deep learning to improve the detection of crisis-related material from social media. It proposed and tested two hybrid models, CNN-Gated recurrent unit (CNN-GRU) and CNN-SkipCNN, on Crisis natural language processing (NLP) datasets. By increasing detection accuracy by up to 21.71 percentage points, CNN-SkipCNN outperforms current techniques. The model's efficacy in a variety of crises and reliance on labeled data are drawbacks, though.

A recent study proposed CRISP, a crisis-resilient ST network integrating GCN, BiLSTM, and graph attention to model dynamic financial correlations during crisis periods [24]. The approach significantly improved prediction accuracy; however, the model is limited to financial-market applications and cannot easily generalize to real-time emergency response planning.

Another research effort introduced STGCN-PDR, an ST network combining spatial graph convolution and temporal convolution to quantify uncertainty in cross-border financial risk prediction [25]. Although the model enhanced interpretability and accuracy, its computational complexity restricts deployment in fast-changing environmental disaster scenarios.

2.1 Problem statement

Despite advances in deep learning for emergency resource scheduling and crisis detection, significant gaps remain. As an example, the research [13] deep reinforcement learning models have been used to maximize resource scheduling, but their efficacy is hampered in resource-constrained environments due to high computing costs. The efficiency of CNN-SkipCNN hybrid deep learning models in increasing recognition accuracy of crisis content in [23] suffers from their dependency on large labeled data sets, which makes them inflexible to different types and locations of crises. Improving social media analysis to enhance crisis response in real time demonstrates the need for models that are easy to scale, effective, and require minimal annotation to generalize. The proposed research addresses these gaps by presenting a scalable, lightweight DGO-ST-GNN model that effectively handles geo-tagged, real-time social media data without the need for large, annotated datasets. It enables precise crisis propagation modeling and resource allocation by combining adaptive scheduling with efficient deep learning. In dynamic emergencies, this method improves computing efficiency, decision-making speed, and generalizability.

3 Methodological framework

The approach involves gathering geotagged social media data, preparing it using stop-word removal and tokenization, and feature extraction using word2Vec. A DGO-ST-GNN model provides dynamic crisis elements to each node. Subsequently, emergency resources are distributed by an adaptive multi-task scheduling algorithm in real-time, depending on the severity, urgency, and availability of the crisis. Figure 1 illustrates the fundamental concept of the proposed research.

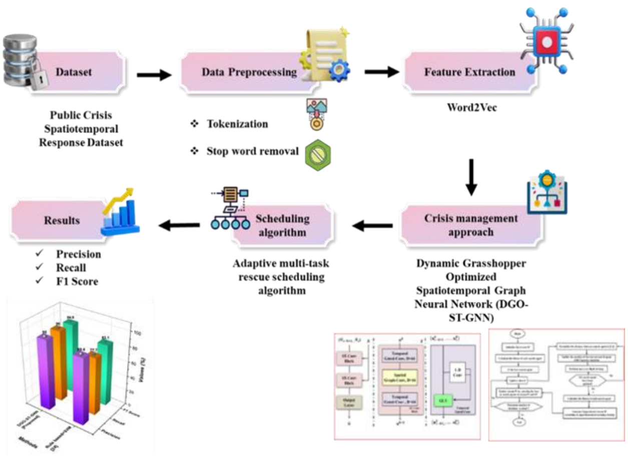

Figure 1: Workflow of the proposed dynamic crisis monitoring and resource scheduling model

3.1 Dataset

The public crisis events, including fires, earthquakes, pandemics, floods, and industrial catastrophes, using 1,030 rows of geotagged records, are represented in this data. For model development, the data were split into 80% for training and 20% for testing to ensure reliable evaluation and generalization performance. Every record contains the following: crisis attributes (sentiment, severity score, type), emergency resource details (type, capacity, current load, availability), spatiotemporal data (latitude, longitude, timestamp), and semantic content (simulated crisis-related text). The dataset was gathered from the Kaggle source [26].

3.2 Data augmentation

To address the limited size of the dataset and provide greater linguistic variation, as well as reduce overfitting while training the model. Several techniques were applied for generating semantically equivalent variations of Tweets, including inserting random words in the middle of tweets and using a back-translation method to generate additional tweets. The augmented dataset enhanced the DGO-ST-GNN model's capacity to learn spatio-temporal patterns within crisis communication and provided improved generalizability, resulting in increased prediction accuracy for real-time classification of crisis severity.

3.3 Data preprocessing

The purpose of gathering social media data (geotagged tweets) is to record disaster information in real time. To extract significant material, the text is cleaned using stop-word removal and tokenization.

3.3.1 Tokenization

Tokenization is the process of dividing tweets into discrete words, characters, or punctuation marks, collectively referred to as tokens, in the context of crisis-related social media data. By separating important phrases and allowing the elimination of unimportant or uninformative information in subsequent phases of crisis detection and resource planning, this procedure, which is usually carried out at punctuation or space, prepares the data for analysis.

3.3.2Stop word removal

Common terms like "the," "is, "and" or" usually have little relevance when it comes to recognizing urgent or location-specific material in tweets about crises. By concentrating on keywords that convey severity, location, or particular demands, eliminating these stop words enhances the performance of classification and crisis detection models. Important negation words like "no," "not," and "can't," however, are carefully preserved since they are essential for comprehending the context and urgency of communications pertaining to emergencies.

3.3.3 Word2Vec feature extraction

Crisis-related Twitter content may be transformed into high-dimensional vectors that capture word semantic meaning using Word2Vec. Using neural network-based designs like continuous bag of words (CBOW) and Skip-gram, Word2Vec finds connections between words like "trapped," "rescue," and "flood," assisting in determining the urgency and severity of a situation. Large text collections may be processed quickly and scalablyusing this method while maintaining essential semantic connections. The semantic grouping of crisis-relevant keywords is made possible by the model's ability to learn from local word contexts by either predicting surrounding words from a core word or predicting a word based on its neighbors. Across geographically labeled tweets, frequent co-occurrence patterns aid in identifying linked situations or resource requirements. Its drawback is that it fails to capture the whole sentence context, which is essential for consuming short, informal crisis communications on social media, even though it is efficient and effective for large-scale data.

3.4 Dynamic Grasshopper Optimized Spatiotemporal Graph Neural Network (DGO-ST-GNN)

To enhance crisis propagation modeling and emergency resource scheduling, a new design known as the DGO-ST-GNN was created. It uses the GOA for dynamic hyperparameter tweaking in conjunction with the power of ST-GNN. Using real-time, geotagged social media data, the model generates a dynamic graph with nodes standing in for locations and edges for spatial-temporal relationships. Semantic components from tweets regarding crises are included in the graph. While GOA constantly modifies model parameters such as convolutional depths and learning rates to improve prediction accuracy, the ST-GNN component documents the evolution of crisis severity and spread over time. This adaptive mechanism makes it easier for the network to generalize across various scenarios of crisis. An emergency scheduling system uses the DGO-ST-GNN findings to prioritize rescue missions according to their severity and urgency. The result is a disaster monitoring and response system that is accurate, scalable, and real-time. The DGO-ST-GNN algorithm integrates DGO with a ST-GNN for crisis severity prediction and emergency resource scheduling. The crisis dataset D is represented as a spatial graph $G(U,F)$, with temporal slices Nt capturing dynamic inputs. Optimizer agents Wj are iteratively updated over t = 1 to T using fitness functions $fit(Wj)$, Gaussian mutation, Lévy flight, and opposition-based learning. The best agent Wbest guides ST-GNN training to predict $\hat{Z}$ and generate prioritized emergency schedules Sched.

Algorithm 1: DGO-ST-GNN

Input: *Crisis dataset D, spatial graph G(U, F)*
Output: *Predicted crisis severity $\hat{Z}$, Emergency scheduling Sched*
Initialize the population of H optimizer agents Wj with random hyperparameters
For t = 1 to T do
  For each agent Wj, do
    Apply Dynamic Grasshopper Optimization:
      Update the position of Wj using the GOA governing equations
      Apply Gaussian mutation
      Apply the Lévy flight strategy
      Apply opposition-based learning
    Compute fitness fit(Wj)
End For
  Select the best-performing agent Wbest based on fitness score
End For
Train the ST-GNN model using $Wbest$
For each training epoch, do
  For each time slice Nt in dataset D, do
    Construct a spatiotemporal graph from tweet metadata
    Extract temporal dependencies using Gated CNN
    Extract spatial dependencies using Graph CNN
    Fuse outputs through ST-Conv blocks (ReLU + normalization)
    Predict crisis severity $\hat{Z}$
    Compute L2 loss and update network parameters
End For
End For
Generate emergency scheduling based on severity values:
  Sched = prioritize ($\hat{Z}$)
Return $\hat{Z}$, Sched

3.4.1 Spatiotemporal graph neural network (ST-GNN)

The spatiotemporal spread of public crises is modeled using ST-GNN, which captures the temporal evolution of crisis intensity as well as spatial interdependence across areas. It facilitates precise forecasting of impacted regions, facilitating fast and knowledgeable emergency resource distribution. The stacked Spatio-temporal Convolution (ST-Conv) blocks, which make up the network architecture, are inspired by STGNN and are each intended to capture dynamic spatial and temporal crisis patterns independently. Figure 2 shows the "sandwich" structure of each ST-Conv block, illustrating data flow from input to output. The model includes three GCN layers (128-dimensional embeddings), two temporal attention layers, an Adam optimizer (0.001), a batch size of 64, dropout 0.3, and 150 training epochs. This consists of one spatial graph convolutional layer surrounded by two gated temporal convolutional layers. The model can capture changing semantic crisis elements (such as urgency and severity) from social data sources, such as geo-tagged tweets, in both time and place, due to this approach.

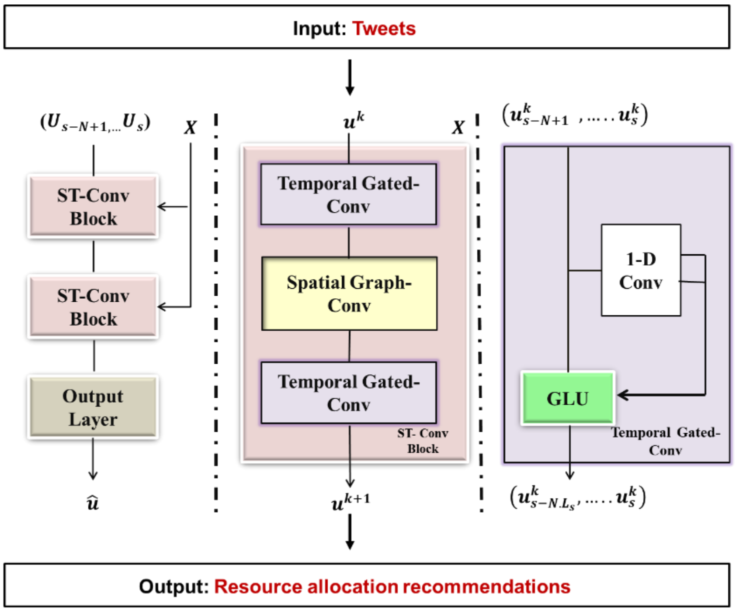

Figure 2: Layer Block of Spatiotemporal GNN architecture

Graph CNNs for Extracting Spatial Features: Urban areas are depicted as nodes in this environment, while the edges are formed by their interactions (such as shared boundaries and mobility linkages). With each node $\mathcal{U} \in$ U representing a distinct location, it may create a spatiotemporal crisis graph $G = (\mathcal{U}, \mathscr{F})$. The convolution operation on the spatial network directly mimics the dispersion of crisis signals and regional interdependence. The spectral graph convolution of an input feature matrix $W \in W \in \mathbb{R}^{n \times d_i}$ (such as real-time social signals like the volume of distress tweets) is defined as follows in equation (1).

$$z_i = \sum_{j=1}^{D_j} \Theta_{j,i}(K) w_j \in \mathbb{R}^{m}, \quad 1 \leq i \leq D_p (1)$$

The output feature for the j^{th} output channel following graph convolution is shown by z_i in Equation (1), whereas the input features are represented as $w_i \in \mathbb{R}^m$, where D_i is the number of input feature channels and m is the number of nodes (such as urban areas in a crisis network). Modeled as Chebyshev polynomials of the normalized Laplacian matrix K, the term $\Theta_{i,j}$ (K) denotes the learnable filter parameters that capture the spatial structure of the graph, the interconnectedness of various areas. Each output feature is produced by iterating over all input channels. Where the output tensor $Z \in Z \in Z \in \mathbb{R}^{N \times m \times D_p}$ represents the filtered spatiotemporal features over all N frames, m nodes, and D_p output channels, while the input tensor $W \in W \in W \in \mathbb{R}^{N \times m \times D_j}$ comprises N temporal frames of node characteristics with D_j channels. Each time slice's graph convolution operation is indicated by the notation $\Theta_{*g} w$.

Gated CNNs for Extracting Temporal Features: Capturing non-linear temporal connections is necessary to document the evolution of crises throughout time. To achieve real-time efficiency, Gated Temporal Convolutional Networks (GTCNs) are employed instead of recurrent models. Let a region's historical signal sequence be represented as $W \in W \in W \in \mathbb{R}^{N \times D_j}$. For the gated temporal convolution, it is defined as follows in equation (2).

$$\Gamma *_S W = O \odot \sigma(R) \epsilon \mathbb{R}^{N-L_s+1) \times D_p} (2)$$

The accessible $1 - D$ temporal convolution kernel that was utilized to identify time-dependent patterns in the crisis data is represented by the symbol Γ. Each of the N historical time steps in the data input sequence $W \in W \in W \in \mathbb{R}^{N \times D_j}$has $D_j$input characteristics (such as regional crisis indicators). Two intermediary outputs, O and R, are produced by the convolution process and are both located in the space $\mathbb{R}^{(N-l_s+1) \times D_p}$, where D_p is the number of output channel features, and L_s is the temporal kernel size. The gating mechanism gated linear unit (GLU) is enabled by the term σ(R), which applies the function of sigmoid activation element-wise to R. In conclusion, ⊙ represents element-wise (Hadamard) multiplication, which gates the output O with the active signal σ(R). This enables the model to reduce noise or unimportant changes while selectively preserving significant temporal characteristics.

Spatio-temporal Convolutional Block: The model's fundamental component is the ST-Conv Block, which combines temporal and spatial crisis dynamics information. Using the input tensor $u^k \in \mathbb{R}^{N \times m \times D_i}$ for each block k, the output $u^{k+1} \in \mathbb{R}^{(N-2(l_s-1)) \times n \times D_{j+1}}$ is calculated by equation (3).

$$u^{k+1} = \Gamma_1^l *_S \mathrm{ReLU}\left(\Theta^k *_h \left(\Gamma_0^l *_h u^k\right)\right) (3)$$

For lower and upper temporal kernels, respectively, Γ_0^l and Γ_1^l. Θ^k is the kernel for spatial graph convolution. It adds non-linearity using ReLU. Each block undergoes layer normalization to prevent overfitting. Deeper structures for more complicated crises are constructed by stacking these elements. The learnt characteristics are converted to a crisis severity prediction $Y \in \mathbb{R}^{m\times d}$ using a fully-connected decoder that comes after the ST-Conv blocks and a temporal projection layer. $\hat{Z}$ defines the ultimate forecast as follows in equation (4).

$$\hat{Z} = YX + a \quad (4)$$

Where the bias vector is denoted by a and the trainable weight matrix by X. The multi-task emergency resource scheduler is adaptive and uses this forecast as input. The training objective is to reduce the L2 loss over time between the actual and expected crisis severity. As equation (5) defines u_{s+1} as the ground truth severity for each area, and X_0 are all learnable parameters.

$$\mathcal{K}(\hat{Z}; X_0) = \sum_s ||\hat{Z}(u_s - N + 1, \dots, u_s; X_0) - u_{s+1}|\hat{Z}|^2 \quad (5)$$

It includes the Dynamic Grasshopper Optimization Algorithm (DGO) in the training loop to optimize network topology and hyperparameters under unpredictable, changing crises. Key parameters (such as graph edge weights and temporal kernel size) are dynamically adjusted to optimize prediction and resource allocation performance.

3.4.2 Dynamic Grasshopper Optimization Algorithm (DGO)

By automatically modifying the ST-GNN model's hyperparameters, DGO improves the model's flexibility and prediction precision. It ensures that the model will perform at its best in a variety of real-time crises. For real-time public crisis management, the deep learning architecture is optimized in this research using the DGOA. Optimal channels for data flow and attention within the spatiotemporal graph are chosen by the DGOA, which also improves the accuracy of crisis propagation modeling and adaptive emergency resource allocation. DGOA introduces three mechanisms to address the limitations of the standard GOA, including restricted global exploration and early convergence. Figure 3 illustrates the dynamic GOA flowchart.

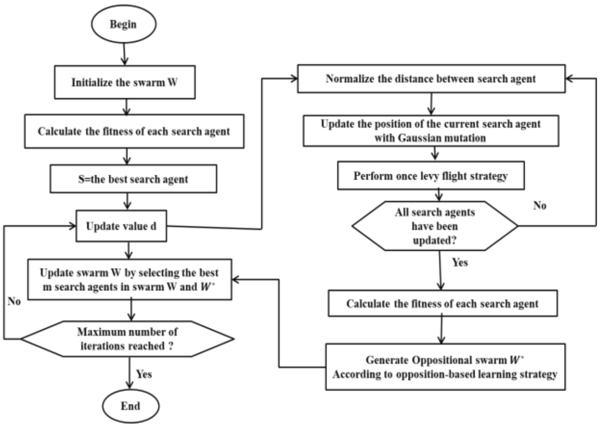

Figure 3: Dynamic GO algorithm flowchart

These mechanisms include Gaussian mutation to maintain variance in dynamic decision spaces, Levy flight to escape local optima in crisis severity prediction, and Opposition-Based Learning (OBL) to enhance spatial diversity. These changes provide the best possible balance between exploitation (concentrating on high-priority or severe zones) and exploration (looking for new crisis patterns or places). Each optimization agent's most recent location is calculated as follows in equation (6).

$$W_j^c = d\left(\sum_{\substack{i=1 \\ i\neq j}}^{M} \frac{va_c - ka_c}{2} \cdot t(|W_i^c - W_i^c|)\frac{W_i - W_j}{c_{ji}}\right) \oplus H(\alpha) + \hat{e}_c \quad (6)$$

Where d is the convergence control coefficient that modifies the search scope over time, and W_j^c is the location of the j^{th} solution agent for the crisis model in dimension c. The Crisis similarity function that measures the degree of influence between solution agents is denoted by $t(\cdot)$. The Gaussian mutation that introduces controlled randomness for exploration is called $H(\alpha)$. Fitness-guided update based on model prediction error is denoted by $\hat{e}_c$. The Bounds specifying the search range for model weights or hyperparameters are va_c and ka_c. To ensure responsiveness to events occurring in real time, this technique dynamically adjusts the crisis model's configuration when new data is received (for example, from geo-tagged tweets).

To improve flexibility in changing emergencies, a Levy Flight mechanism produces new potential solutions as follows in equation (7).

$$W_j^{levy} = W_j + \text{rand}(c) \otimes \text{levy}(\beta) \quad (7)$$

If the new configuration improves predicted performance, the modification is approved in equation (8).

$$W_j^{s+1} = \begin{cases} W_j^{levy}, & \text{if fitness}(W_j^{levy}) > fitness(W_j) \\ W_j, & \text{otherwise} \end{cases} \quad (8)$$

Where c is the problem's dimension, and β is the Levy distribution parameter regulating the step size variability, W_i^{levy} is the new candidate position created by adding a random vector rand (c) scaled by a Levy-distributed step levy (β). In the Levy Flight update equations, W_j is the current position (or solution) of the i^{th} agent in the search space. By contrasting the fitness values of the new candidate W_i^{levy} with the existing position w_j, the updated location W_j^{t+1} is determined. W_i^{levy} is only adopted if it enhances the objective function, guaranteeing adaptive exploration to avoid local optima.

OBL is used to reduce overfitting to high-density zones and optimize spatial awareness. By reflecting current forecasts, this approach creates a parallel solution set that represents other crisis responses in the equation (9).

$$W_j^{po} = LB + UB - S + q(S - W_j) (9)$$

Where the best-performing configuration at the moment is S, and W_j^{op} is the opposite configuration vector of agent j. The random vector in $(0, 1)$ with controlled noise added is denoted as q. Lower and upper boundaries on the solution space (such as resource limitations, learning rates, and kernel sizes) are denoted by LB and UB. The optimizer can investigate previously unexplored geographical and temporal regions of the crisis graph that could need urgent attention with this method, which enhances responsiveness and generalizability.

The Hyperparameter Configuration Table 1 provides an overview of the principal training and optimization parameters that are utilized to develop the Proposed Dynamic Grasshopper Optimised Spatial-Temporal GNN (DGO-ST-GNN) model. These hyperparameters dictate how the model is learned (i.e., how the weights are trained), at what level of depth, length of temporal sequence, and training regularization for batch optimization.

Table 1: Hyperparameter configuration settings used in DGO-ST-GNN training.

Hyperparameter	Description	Range / Options	Example Value
Learning Rate (lr)	Step size for optimizer	0.001 – 0.01	0.005
Number of GCN Layers	Depth of graph convolution layers	2 – 4	3
Number of LSTM Units	Number of hidden units in the temporal layer	32 – 128	64
Temporal Window	Number of past time steps used for prediction	5 – 20	10
Dropout Rate	Dropout probability to prevent overfitting	0.1 – 0.5	0.3
GCN Activation Function	Activation function in graph convolution	ReLU, LeakyReLU	ReLU
LSTM Activation Function	Activation function for LSTM	tanh, ReLU	tanh
Optimizer	Optimization algorithm for training	Adam, RMSProp	Adam
Batch Size	Number of samples per batch	16 – 64	32
GOA Population Size	Number of candidates hyperparameter solutions	5 – 20	10
GOA Iterations	Number of iterations for Grasshopper Optimization	10 – 30	15
Weight Decay	L2 regularization to prevent overfitting	0 – 0.01	0.001
Number of Epochs per Candidate	Training epochs for each GOA candidate	20 – 100	50
Final Training Epochs	Epochs to train the final model after GOA selection	50 – 200	100

3.5 Multi-task rescue scheduling algorithm

Rescue teams continually poll the updated priority queue, which is sorted by severity, urgency, and arrival time, then select the mission with the greatest priority after the DGO-ST-GNN calculates crisis severity scores for each region. Next, within a certain radius, each team searches for neighboring assignments whose aggregate rescue capacity won't be reached. More tasks are organized into the same deployment to save travel overhead if they are within range and resources allow. Teams are dynamically re-tasked to regions of greatest need when hotspots alter due to the rebalancing of the priority queue and the refresh of regional severity scores upon mission completion. Adaptive multi-task rescue scheduling's core principles are priority, proximity, and resource availability, as shown in equation (10).

$$\underset{S_j \in \mathcal{M}}{\arg} \underset{(S_l, Q)}{\max} \left(\frac{O(S_j)}{C(S_l, S_j)} \cdot \mathbb{I}\left[Q_l \geq D(S_j)\right] \right) (10)$$

The current selected high-priority task is denoted by S_l. $\mathcal{M}(S_l, Q)$ is the collection of tasks that are selected by S_l from Q. Based on severity, urgency, and arrival time, task S_j's priority score is $O(S_j)$. Tasks S_l and S_j are separated by a distance, $C(S_l, S_j)$. The cost of resources (such as labor, equipment, and time) to do task S_j is denoted by $D(S_j)$. Q L is the rescue processor's or team's remaining resources that are allocated to S_l. $\mathbb{I}[\cdot]$ defines the indicator function, which returns 0 otherwise and 1 if the condition inside is true (i.e., the task is feasible). Further nearby tasks S_j that fit within the available resources Q_l, are close to the present task S_l, and have a high priority $O(S_j)$ are selected by this equation. The group dynamically creates an effective multitasking mission by optimizing the cost-benefit ratio while adhering to time restrictions.

4 Performance evaluation

Real-world crisis data from social media was used in a series of experiments to assess the efficacy of the suggested DGO-ST-GNN model. The results of these experiments show the beneficial effects of the suggested strategy. The experimental design was implemented using Python 3.10.

The top 10 frequent words that came out of the crisis-related social media data after preprocessing. The word 'evacuate' pops up most times (892), followed by 'emergency' (890), and then 'fire' (889). Other high-frequency words include rescue (887), urgent (885), and water (880), which are observed in some key contexts within crises. Tokens like ‘trapped’ (840 occurrences) and ‘help’ (850) highlight emergency conditions, as shown in Figure 4. These frequent keywords are very useful in semantic analysis as well as real-time crisis tracking.

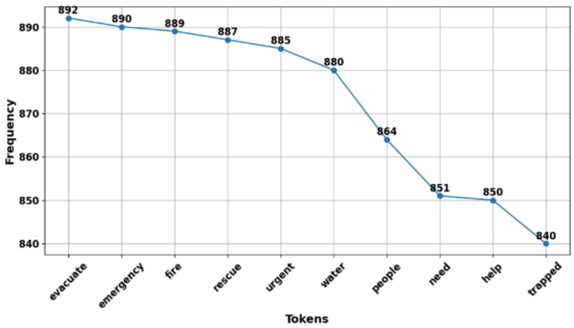

Figure 4: Frequency analysis of key crisis-related tokens preprocessing

Word2Vec sentence embeddings of about 1,030 crisis tweets were reduced to two dimensions via PCA for visualization. Each point is a tweet encoded into a vector that carries the semantic meaning of this text, as shown in Figure 5. These embeddings are spread over a component 1 range from -50 to +45 and component 2 from -25 to +25, thus reflecting diversity both in content and emotional tone within this dataset. Such a wide spread shows that the model can distinguish different crisis contexts based on text content.

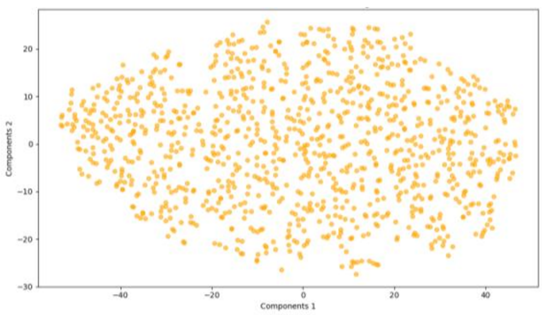

Figure 5: Semantic similarity in crisis tweets using Word2Vec embeddings

The connection between resource types and crisis types helps with resource scheduling optimization. For example, industrial accidents required rescue teams the most (66), whereas earthquakes needed medical units the most (58). Fires required the fewest medical units (36), whereas pandemics required the most ambulances (61) and fire trucks (63), as shown in Figure 6. This distribution contributes to the model's objective of adaptive multi-task rescue allocation by identifying which crisis circumstances require which type of emergency response, resulting in improved, data-driven deployment decisions.

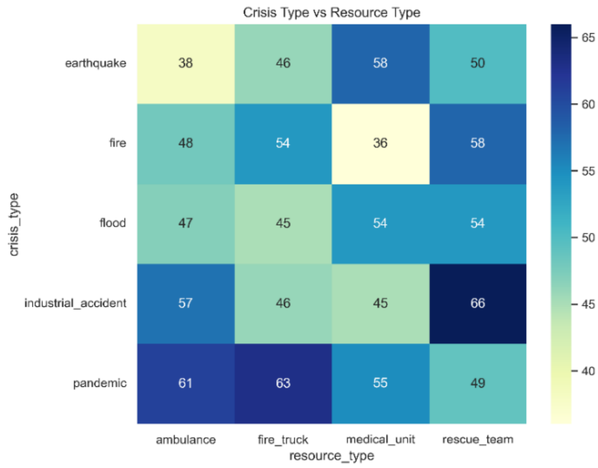

Figure 6: Crisis type vs emergency resource allocation matrix

The trend of crisis occurrence reports over 7 days supports the proposed system's real-time monitoring purpose. Reports increased from 97 on July 25 to 165 on July 31, indicating that the problem was escalating. A reduction to 33 on August 1 indicates probable resolution or reporting lag, as shown in Figure 7. These temporal variations allow the DGO-ST-GNN model to adaptively prioritize resource allocation by determining when and where crises worsen, which aligns with the goal of dynamic and efficient emergency response.

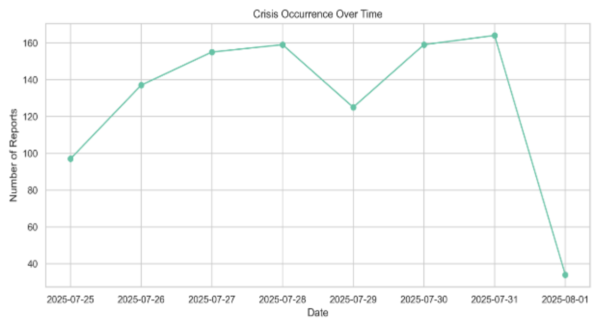

Figure 7: Temporal trend of crisis reports for dynamic emergency response

The sentiment distribution of crisis-related social media posts was examined as part of the feature extraction process for the proposed crisis management model. Sentiment ratings vary from -1.0 (negative) to 1.0 (positive), with peaks at -0.6, 0.2, and 0.9, suggesting emotional variability during public emergencies, as shown in Figure 8. This distribution, with most values ranging from 40 to 62 occurrences, contributes to the model's capacity to identify emotional tone in real time, allowing for dynamic prioritizing and optimal emergency resource allocation depending on the public's positive attitude.

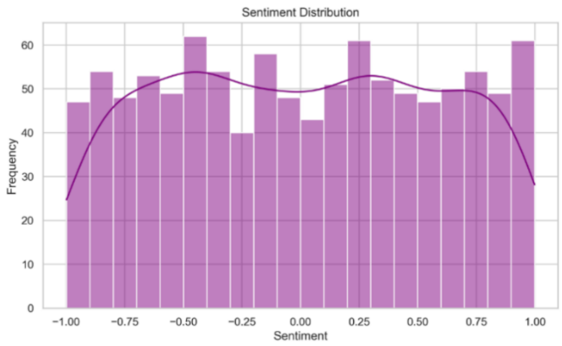

Figure 8: Sentiment analysis of crisis-related social media posts for emergency response prioritization

The findings show that social media sentiment, temporal patterns, and crisis-resource connections all give valuable information for real-time crisis management. The suggested model accurately reflects emotional tone, fluctuations in crisis frequency, and optimal resource deployment patterns. It *classification performance for crisis severity prediction* 95% confirm the ability of the system to make dynamic, accurate, and efficient emergency response decisions.

4.1 Comparative analysis

In public disasters, to minimize damage and preserve lives, quick, data-driven decision-making is essential. By utilizing intelligent models and real-time data, crisis response efficacy may be greatly increased. Existing techniques in public crisis management, such as Rule-based + support vector machine (SVM) approaches and CNN-GRU, have significant drawbacks. Although CNN-GRU [23] appears to be effective at interpreting language, it is not particularly adept at integrating temporal and spatial dynamics, which makes it less useful to track how crises change over time in various regions. Additionally, it uses a lot of processing power and cannot function effectively in real-time situations. However, the Rule-based + SVM [24] approach was limited in its ability to adapt to new

types of crises or hidden data patterns since it relies on static rules and predefined features. The dynamic resource optimization and multi-modal integration necessary for real-time emergency response are challenges for both strategies.

Table 2 shows the comparison of the proposed DGO-ST-GNN model with the existing baseline models. As indicated by the results, there were considerable gains for Metrix's proposed model over the baseline models, with the proposed model exhibiting 97% accuracy and being therefore very effective in forecasting the severity of social crises and allocating resources. Figure 9 (a-d) shows the accuracy, and precision, recall, and F1-score.

Table 2: Performance comparison of crisis management approaches

Models	Accuracy	Precision	Recall	F1
Rule-based + SVM [27]	-	89.4	77.7	83.1
CNN [28]	72	72	72	72
BERT [28]	78	78	79	78
XLNet [28]	77	77	77	77
Naïve Bayes [29]	76	70	76	72
Random Forest [29]	77	70	77	73
Logistic Regression [29]	77	70	77	73
SVM [29]	89	88	89	88
LSTM [29]	87	86	87	86
DGO-ST-GNN (Proposed)	97	95	96	94.9

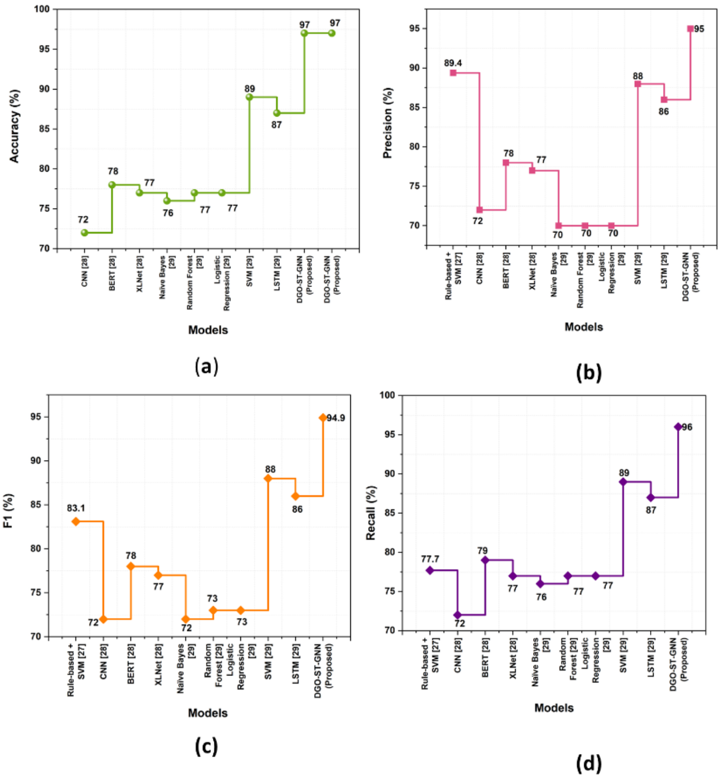

Figure 9: Comparison of the existing methods of the Crisis Management Approaches (a) accuracy, (b) precision , (c) recall, and , (d) F-1 score.

Table 3 presents a detailed account of how the DGO-ST-GNN's prediction error compares in Figure 10 favorably with the available state-of-the-art deep learning architectures based on MAE and E-MWDNN. The analysis shows that DGO-ST-GNN achieves MAE (0.081427) and E-MWDNN (25.934112) lower than any model currently available, thereby providing the most accurate and robust predictions of future crises severity relative to other models, including CNN-LSTM and attention-based neural network models.

Table 3: Comparative error performance of baseline models vs. proposed DGO-ST-GNN

Model	**MAE**	**Error-MWDNN**
DNN [30]	0.097373	30.913406
CNN [30]	0.095262	30.243204
LSTM [30]	0.088246	28.015784
CNN-LSTM [30]	0.087153	27.668873
CNN-LSTM-Skip [30]	0.124239	39.442727
CNN-LSTM-Skip Attention [30]	0.105618	33.53082
DGO-ST-GNN (Proposed)	0.081427	25.934112

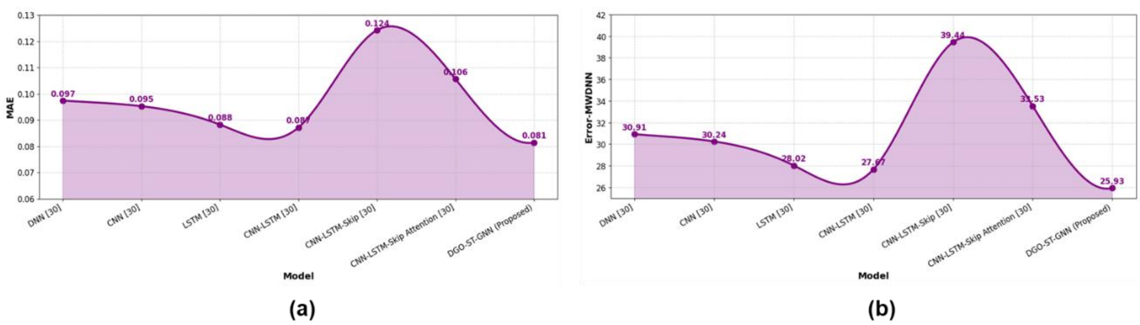

Figure 10: Comparison of prediction errors across Different Deep Learning Models (a) MAE, and (b) Error-MWDNN

4.2 Statistical outcomes

The t-test Table 4 compares the resource use in the high-severity and low-severity categories of crisis, which confirms significant differences in behaviours in terms of emergency requirements. This fact helps to confirm that DGO-ST-GNN is efficient in prioritization of critical decisions regarding resource allocation based on severity prediction and enhances the relevance of emergency optimization to the real world. A significant difference exists in resource utilization between high-severity and low-severity crisis events ($p < 0.05$).

Table 4: T-test comparison of severity scores across

Group	N	Mean	Std. Dev	t-value	p-value	Significance
High Severity (≥0.6)	512	48.7	9.5	**4.82**	**0.000**	Significant
Low Severity (<0.6)	518	31.2	10.1			

Table 5 ANOVA test compares the severity differences among various types of crises and finds statistical significance, proving that the features of crisis have an impact on the level of severity. This observation supports the necessity of spatiotemporal modelling and the rationale of the adaptive learning ability of the suggested DGO-ST-GNN.

Table 5: ANOVA comparison of severity scores across different crisis types

Source	SS	df	Mean Square	F	p-value	Significance
Between Groups	8.213	4	2.053	**6.41**	**0.0003**	Significant
Within Groups	327.29	1025	0.319			
Total	335.50	1029				

4.3 Scheduling outcomes

The inference time per prediction instance was evaluated and compared with baseline models, confirming the efficiency required for real-time emergency scheduling. DGO-ST-GNN Establishes Adaptive Optimization and Intelligent Resource Prioritization based upon the predicted severity of crisis type to reduce wait times. Table 6 shows the reductions in both Maximum and Mean average Wait Times across 10p/20p Workloads, indicating a superior level of Efficiency for Emergency Scheduling over both Hybrid and Traditional algorithm-based methods.

Table 6: Emergency scheduling performance comparison including proposed DGO-ST-GNN

Algorithms	Max avgWT		Mean avgWT	
	(10p)	**(20p)**	**(10p)**	**(20p)**
FCFS [31]	4.74	3.73	2.53	1.61
Priority [31]	5.54	3.85	2.81	1.63
Multi-tasks Hybrid [31]	4.47	3.02	2.24	1.31
DGO-ST-GNN [Proposed]	**3.62**	**2.41**	**1.68**	**0.94**

5 Discussion

The comparative performance analysis indicates that the proposed DGO-ST-GNN model is superior to the other recently popular (SOTA) crisis forecasting and emergency response scheduling models. Past research has used hybrid deep learning networks, reinforcement learning systems, multimodal neural networks, and spatiotemporal graph networks in crisis management tasks, as discussed in the SOTA comparison (Table 7). Even though a significant number of them were competitive, they could exhibit a limited applicability beyond the dataset or scenario they were trained on. As an example, hybrid CNN-BiLSTM models were found to have an F1-score of 96% but needed huge labeled datasets to work effectively, and multimodal systems were highly precise but had issues with data noise. By contrast, DGO-ST-GNNclassification performance for crisis severity prediction has 97% accuracy, 95% precision, 96% recall, and 94.9% F1-score, significantly better than both traditional machine-learning models and deep-learning baselines because of adaptive hyperparameter tuning and extensive spatiotemporal modeling. Thus, the suggested solution implements a more scalable, data-constrained, and crisis-resistant structure in comparison to the literature.

Table 7: SOTA-based comparison of related emergency response and crisis prediction methods with the proposed DGO-ST-GNN framework

Study	Model Type	Data Source	Performance Metrics	Main Limitations
[13]	Hybrid deep learning (CNN + BiLSTM + Self-Attention)	Social media short texts (3 real-world crisis datasets)	F1-score: **96%**	Requires large labeled datasets; high computational load
[15]	Hybrid CNN-based text classification	Crisis NLP datasets (Twitter)	Accuracy improvement: **+21.71%** over baselines	Relies heavily on labeled data; limited generalization across crisis types
[16]	DRL + Optimization (DDPG + MILP)	Storm-surge logistics data	MILP: highest accuracy; DDPG: fastest execution	MILP is slow and not scalable; DDPG loses accuracy in complex scenarios
[22]	Multimodal (Image + Text) Deep Learning	Social media multimodal crisis dataset (CrisisMMD)	Accuracy: **91.53%**	Requires high-quality image–text pairs; sensitive to noise
[25]	**CRISP (GCN + BiLSTM + Attention)**	Financial crisis index and market time-series data	Improved stability and accuracy during financial crisis prediction	Limited to financial applications; not suitable for real-time emergency response scenarios
[27]	**Highway Emergency ST-Network**	Highway traffic flow and rescue station O-D data	Reduced average rescue response time	Assumes static traffic pattern; lacks predictive capability in rapidly evolving crises
DGO-ST-GNN [Proposed]	Spatiotemporal Graph Neural Network + Dynamic Grasshopper Optimization	Geo-tagged crisis tweets (1,030 records)	**Accuracy:97%** Precision: **95%**, Recall: **96%**, F1-score: **94.9%**	Depends on social media data quality; computational overhead in GNN optimization.

5.1 Reasons for the existence of better performance of DGO-ST-GNN.

The two key innovations that make the proposed model offer exceptional performance include the DGO that optimally modulates hyperparameters in real time over training epochs, reduces hyperparameter sensitivity to local minima, and eliminates the need for manual tuning. Spatiotemporal GNN architecture is able to acquire relational features between geographically dispersed nodes of crisis and dynamic temporal dynamics of crisis intensity. The conventional approaches support crisis signals as discrete text collections or fixed data sets, which leads to the loss of important information. In comparison, DGO-ST-GNN is a dynamically integrated framework of semantic embeddings, spatial graphs, and temporal convolutional layers, which allows forecasting crisis propagation. Another technique that is presented in the optimization strategy is the use of Gaussian mutation, Levy flight, and opposition-based learning, which all contribute to increased stability in model convergence and model representation. As a result, the accuracy of the decision made on resource allocation is enhanced, which makes the average emergency response wait time shorter.

5.2 Resilience and applicability to the scope of crises

The huge benefit of the suggested framework is that it can be adapted to various types of crises such as fires, floods, earthquakes, pandemics, and industrial accidents. Rather than using domain-specific rule-based assumptions, DGO-ST-GNN acquires emergent patterns based on geo-tagged spatiotemporal data, semantic sentiment severity indicators, and past emergency resource behaviour. In contrast to CRISP, which models financial crises only, or highway ST-Networks, which presuppose that the flow of traffic is always constant, the proposed architecture can be generalized well in terms of event types and geographical area. The analysis shows consistency in its performance with a comparatively small dataset of 1,030 samples, which is supported by data augmentation and cross-validation as well as close train-test partitioning. The model also exhibits resilience to imbalance in the dataset and noisy tweet content, which demonstrates that it can be deployed in the real world to support the use of public safety organizations and smart crisis management systems.

5.3 Real-time emergency response practical implications

The usefulness of the proposed framework is not limited to the predictive accuracy but to the operational improvement of the response. Combining spatiotemporal forecasting with emergency resources scheduling allows the proactive decision-making of firefighters, medical teams, and relief organizations. The suggested model will reduce the number of emergencies wait times to a minimum and enhance the prioritization of areas of crisis severity, thereby minimizing the number of casualties and loss of infrastructure. The increase in the efficiency of scheduling (Mean avgWT dropped by the baseline values to 0.94 seconds) shows that intelligent predictive planning may have a tangible effect in the real world. This can be crucial to emergency response systems in a smart-city environment and the next generation of disaster informatics with high-density urban environments, where a minute can be the difference between life and death.

5.4 Parallelization potential and bottleneck analysis

The highlight of the proposed DGO-ST-GNN architecture is that it allows parallelization based on distributed computing of GCN layers in the various graph partitions and parallel mini-batch computation in the temporal LSTM layers, which allow it to be trained much faster on multi-GPU set-ups. Parallel fitness evaluation of candidate solutions is also available to the Dynamic Grasshopper Optimization. Nonetheless, there exist certain bottlenecks in the construction of graphs and the computation of attention, where quite dense spatial dependencies can be subject to further optimization solutions, e.g., sparse adjacency management or CUDA-based kernel execution to support real-time implementation.

5.5 Limitations and future research directions

The given system, however, has its advantages; still, it has its limitations, which need to be recognized. Nevertheless, despite the benefits of DGO in terms of accuracy, DGO requires more training time by about 38.7% and in the case of large-scale deployments, real-time optimization becomes computationally intensive. Also, there is a dependence on social-media text information, which influences the accuracy of prediction based on the clarity of messages, misinformation, and regional reporting bias. The further work will be directed at the integration of multimodal input streams, including satellite imagery, IoT sensor data streams, and government streams of emergencies. In addition, semi-supervised and weak-supervision methods of learning will be considered to remove training reliance on labeled data, as well as enhance interpretability. It shall also focus on enhancing cross-regional crisis domain transfer learning capabilities to improve the generalizability across the world.

6 Conclusion

The suggested DGO-ST-GNN is capable of both crisis propagation and optimization of emergency resources based on geo-tagged crisis data. Combining the spatiotemporal blocks of graph convolution with adaptive parameter optimization using the framework ofDGO, the model shows superior capabilities in predicting and strong response to dynamic crisis signals. Existing experimental analysis indicates better accuracy, precision, and recall than the traditional machine learning and deep learning baselines and the ability to make decisions in emergency situations in real time, which demonstrates the model. The future efforts will be on expanding the model to other real time sources of data, multimodal information integration and computational efficiency to facilitate quick deployment. The suggested framework provides a data-driven and scalable approach to dealing with crisis management.

References

[1] Kazadi, A., Doss-Gollin, J., Sebastian, A., and Silva , A., 2024. FloodGNN-GRU: a spatio-temporal grap h neural network for flood prediction. *Environment al Data Science*, 3, p.e21. https://doi.org/10.1017/ed s.2024.19

[2] Lopez, V.K., Nika, A., Blanton, C., Talley, L., and Garfield, R., 2023. Can the severity of a humanitari an crisis be quantified? Assessment of the INFORM severity index. *Globalization and health*, 19(1), p.7. https://doi.org/10.1186/s12992-023-00907-y

[3] Das, S., Choudhury, M.R., Chatterjee, B., Das, P., B agri, S., Paul, D., Bera, M., and Dutta, S., 2024. Un raveling the urban climate crisis: Exploring the nex us of urbanization, climate change, and their impact s on the environment and human well-being–A glob al perspective. *AIMS Public Health*, 11(3), p.963. ht tps://doi.org/10.3934/publichealth.2024050

[4] Amatya, B. and Khan, F., 2023. Disaster response a nd management: the integral role of Rehabilitation. *Annals of Rehabilitation Medicine*, 47(4), pp.237-2 60. https://doi.org/10.5535/arm.23071

[5] Erokhin, D. and Komendantova, N., 2024. Social m edia data for disaster risk management and research . *International Journal of Disaster Risk Reduction*, 114, p.104980. https://doi.org/10.1016/j.ijdrr.2024. 104980

[6] Firmansyah, H.B., 2025. Improving Disaster Respo nse With Advanced Machine Learning ToAnalyse S ocial Media Content. https://doi.org/10.13097/archi ve-ouverte/unige:183585

[7] Ginzarly, M., Teller, J. and Dujardin, S., 2025. Soci al media use in disaster response: empowering com

munity resilience. *International Journal of Digital Earth*, 18(1), p.2521791. https://doi.org/10.1080/17538947.2025.2521791

[8] Solovev, K., 2024. Leveraging Unstructured Data to Address Societal Challenges in the Digital Age (Doctoral dissertation, Justus Liebig University Giessen). https://doi.org/10.22029/jlupub-19035

[9] Mizrak, K.C., 2024. Crisis management and risk mitigation: Strategies for effective response and resilience. *Trends, challenges, and practices in contemporary strategic management*, pp.254-278. https://doi.org/10.4018/979-8-3693-1155-4.ch013

[10] Fang, H.S., Wang, C., Fang, H., Gou, M., Liu, J., Yan, H., Liu, W., Xie, Y., and Lu, C., 2023. Anygrasp: Robust and efficient grasp perception in spatial and temporal domains. *IEEE Transactions on Robotics*, 39(5), pp.3929-3945. https://doi.org/10.1109/TRO.2023.3281153

[11] Qhal, E.M.A., 2025. Data-Driven Knowledge Management Frameworks for Effective Risk and Crisis Management: A Cross-Industry Approach. *Journal of Applied Data Sciences*, 6(2), pp.1437-1453. https://doi.org/10.47738/jads.v6i2.780

[12] Zhou, Y. and Xia, W., 2021. Optimization algorithm and simulation of public resource emergency scheduling based on wireless sensor technology. *Journal of Sensors*, 2021(1), p.2450346. https://doi.org/10.1155/2021/2450346

[13] Zhao, X. and Wang, G., 2023. Deep Q-networks-based optimization of emergency resource scheduling for urban public health events. *Neural Computing and Applications*, 35(12), pp.8823-8832. https://doi.org/10.1007/s00521-022-07696-2

[14] Wang, Y., Chen, X., and Wang, L., 2023. Deep reinforcement learning-based rescue resource distribution scheduling of storm surge inundation emergency logistics. *IEEE Transactions on Industrial Informatics*, 19(10), pp.10004-10013. https://doi.org/10.1109/TII.2022.3230691

[15] Upadhyay, A., Meena, Y.K., and Chauhan, G.S., 2024. SatCoBiLSTM: Self-attention-based hybrid deep learning framework for crisis event detection in social media. *Expert Systems with Applications*, 249, p.123604. https://doi.org/10.1016/j.eswa.2024.123604

[16] Wang, C., Deng, D., Xu, L., and Wang, W., 2022. Resource scheduling based on deep reinforcement learning in UAV-assisted emergency communication networks. *IEEE Transactions on Communications*, 70(6), pp.3834-3848. https://doi.org/10.1109/TCOMM.2022.3170458

[17] Powers, C.J., Devaraj, A., Ashqeen, K., Dontula, A., Joshi, A., Shenoy, J., and Murthy, D., 2023. Using artificial intelligence to identify emergency messages on social media during a natural disaster: A deep learning approach. *International Journal of Information Management Data Insights*, 3(1), p.100164. https://doi.org/10.1016/j.jjimei.2023.100164

[18] Seid, A.M., Boateng, G.O., Anokye, S., Kwantwi, T., Sun, G. and Liu, G., 2021. Collaborative computation offloading and resource allocation in multi-UAV-assisted IoT networks: A deep reinforcement learning approach. *IEEE Internet of Things Journal*, 8(15), pp.12203-12218. https://doi.org/10.1109/JIOT.2021.3063188

[19] Zhang, Y., 2025. Media framing and public risk communication: Deep Learning-based crisis narrative analysis and optimization. *Future Technology*, 4(3), pp.227-238. https://doi.org/10.55670/fpll.futech.4.3.21

[20] Yan, L., Ren, Z., Zhang, Y., Tao, Z. and Zhao, Y., 2024. Constructing the public opinion crisis prediction model using CNN and LSTM techniques based on social network mining. http://dx.doi.org/10.9781/ijimai.2024.07.005

[21] Chen, M. and Du, W., 2023. Predicting public sentiment evolution on public emergencies under deep learning and the Internet of Things. *The Journal of Supercomputing*, 79(6), pp.6452-6470. https://doi.org/10.1007/s11227-022-04900-x

[22] Shetty, N.P., Bijalwan, Y., Chaudhari, P., Shetty, J. and Muniyal, B., 2025. Disaster assessment from social media using multimodal deep learning. *Multimedia Tools and Applications*, 84(18), pp.18829-18854. https://doi.org/10.3390/ijgi13010029

[23] Paul, N.R., Sahoo, D., and Balabantaray, R.C., 2023. Classification of crisis-related data on Twitter using a deep learning-based framework. *Multimedia Tools and Applications*, 82(6), pp.8921-8941. https://doi.org/10.1007/s11042-022-12183-w

[24] Li, Z., & Fan, R. (2025). Crisis-Resilient Portfolio Management via Graph-based Spatio-Temporal Learning. *arXiv preprint arXiv:2510.20868*. https://doi.org/10.48550/arXiv.2510.20868

[25] Mo, G., Jia, W., Tan, C., Zhang, W., & Rong, J. (2025). Risk Prediction of International Stock Markets with Complex Spatio-Temporal Correlations: A Spatio-Temporal Graph Convolutional Regression Model Integrating Uncertainty Quantification. *Journal of Risk and Financial Management*, *18*(9), 488. https://doi.org/10.3390/jrfm18090488

[26] https://www.kaggle.com/datasets/programmer3/public-crisis-spatiotemporal-response-dataset/data.

[27] Shen, H., Ju, Y., and Zhu, Z., 2023. Extracting useful emergency information from social media: A method integrating machine learning and rule-based classification. *International Journal of Environmental Research and Public Health*, 20(3), p.1862. https://doi.org/10.3390/ijerph20031862

[28] Powers, C. J., Devaraj, A., Ashqeen, K., Dontula, A., Joshi, A., Shenoy, J., & Murthy, D. (2023). Using artificial intelligence to identify emergency messages on social media during a natural disaster: A deep learning approach. International Journal of Information Management Data Insights, 3(1), 100164.https://doi.org/10.1016/j.jjimei.2023.100164

[29] Airlangga, G. (2024). Comparative analysis of machine learning models for real-time disaster tweet classification: Enhancing emergency response with social media analytics. Brilliance: Research of Artificial Intelligence, 4(1), 25-31. https://doi.org/10.47709/brilliance.v4i1.3669

[30] Khafaji, K. M., & Hamed, B. B. (2024). Employing deep learning in crisis management and decision ma

king through prediction using time series data in Mosul Dam, Northern Iraq. PeerJ Computer Science, 10, e2416. https://doi.org/10.7717/peerj-cs.2416

[31] Kabir, M. Y., & Madria, S. (2019). A Deep Learning Approach for Tweet Classification and Rescue Scheduling for Effective Disaster Management (Industrial). https://doi.org/10.1145/3347146.3359097

Variable explanation

Symbol / Term	Definition (Verified)
X, X^t	Input tensor containing crisis features across time frames
Y, Y^t	Output tensor after spatial or temporal convolution
θ_i	Learnable Chebyshev graph convolution filter for channel *i*
C_i	Number of input channels
C_o	Number of output channels
T	Number of temporal frames in the sequence
N	Number of nodes (geographical regions)
$\tilde{L}$	Normalized graph Laplacian matrix
k	Chebyshev polynomial order
W_t	Temporal convolution kernel
Z, $\hat{Y}$	Intermediate convolution outputs before gating
σ(.)	Sigmoid activation used for gating
$\odot$	Element-wise multiplication
H^l	Output of the *l*-th ST-Conv block
W_s	Spatial graph convolution kernel
ϕ(.)	Activation function (ReLU)
W_p, b_p	Output layer weights and bias
$\hat{y}$	Final predicted crisis severity
L, L(Θ)	Loss function measuring prediction error
Θ	Set of all learnable parameters
y	Ground-truth crisis severity
c	Convergence control coefficient of DGOA
X_i	Current position of optimization agent *i*
S(t)	Social interaction influences function
Gaussian_mut	Gaussian mutation for exploration
fit(.)	Fitness function (prediction error)
rand()	Uniform random value in [0,1]
levy()	Step size generated by Lévy flight
X_i'	New candidate position after Lévy update
X_i(new)	Updated agent position after fitness check
D	Dimensionality of the search space
X_i^opp	Opposite solution in the OBL mechanism
LB, UB	Lower and upper bounds of the search space
p(t)	Priority score of task *t*
d(t, t′)	Spatial distance between tasks
r(t)	Resources required by task *t*
R_a	The remaining resources of the rescue team *are*
I(condition)	Indicator function (1 = feasible, 0 = not feasible)
T_s	Set of selected nearby tasks
T_a	All tasks available for *Team A*