Information Processing and Management 63 (2026) 104442

Contents lists available at ScienceDirect

Information Processing and Management

journal homepage: www.elsevier.com/locate/ipm

Advancing cross-domain emergency classification with multi-view adversarial learning

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ARTICLE INFO

Keywords:
Unsupervised domain adaptation
Cross-domain adaptation
Adversarial optimization
Emergency event
Social media

ABSTRACT

The growing volume of natural and man-made emergency data requires effective real-time classification across various emergency domains on social media. However, current Unsupervised Domain Adaptation (UDA) methods for emergency data classification face two key challenges: predominant grounding in natural disaster contexts that limits generalizability, and difficulty handling domain shifts caused by heterogeneous distributions, linguistic variations, and emotional expressions. To overcome these challenges, we propose Multi-View Adversarial Neural Networks for Robust Unsupervised Domain Adaptation (MARDA), a novel framework that integrates adversarial domain adaptation with multi-view feature learning. First, a cross-view processor consisting of semantic and emotional processors, along with interactive integrators, is designed to generate rich and comprehensive multi-view feature representations. Second, an adaptive weighted domain enhancer is developed to dynamically balance contributions from multiple views, effectively aggregating discriminative information in various domains. Third, an adversarial cross-view optimizer is proposed that employs a minimax game and feature consistency regularization, thereby enhancing cross-domain generalization. Experimental results on four real-world emergency datasets with 24,008 samples show that MARDA outperforms advanced baselines by 7.39% and exceeds large language models by 1.59% in average F1-Score, demonstrating its effectiveness as a generalized solution for cross-domain emergency event classification.

1. Introduction

The intensifying effects of global climate change and rapid urbanization have sharply increased the frequency and impact of natural and man-made emergencies. In 2023, the World Wildlife Fund (WWF) reported the hottest year on record globally (Fund, 2023), highlighting the accelerating climate crisis. This has triggered a surge in extreme weather events, causing widespread disasters. In the United States alone, millions of lives have been disrupted, with economic losses reaching billions of dollars (Washington Post, 2023). From earthquakes and floods to public health crises and social safety incidents, decision-makers must act swiftly to minimize casualties and property damage (Qu & Lyu, 2025). Traditional emergency response strategies rely on smart infrastructure to collect and analyze data from diverse sources like video streams, ground sensors, and satellite imagery (Adeel et al., 2019). However, these

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https://doi.org/10.1016/j.ipm.2025.104442
Received 9 June 2025; Received in revised form 21 August 2025; Accepted 9 October 2025

Available online 15 October 2025

methods often depend on independent actions by victims, experts, and agencies, revealing significant limitations when addressing large-scale, sudden crises (Bunce, Partridge, & Davis, 2012).

The widespread use of social media has highlighted its critical role in emergency events (Qu & Lyu, 2025). Platforms like Twitter and Facebook enable rapid information sharing and provide various data types, including text, images, and videos (Avalle et al., 2024). During natural and man-made disasters, these platforms act as vital hubs for reporting casualties, infrastructure damage, emergency needs, and missing persons (Alam, Ofli, & Imran, 2018, 2018c). However, the diversity and complexity of social media data present significant challenges for efficient processing and analysis (Ding et al., 2025; Myint, Lo, & Zhang, 2024). Especially, China's National Emergency Response Plan for Public Emergencies categorizes emergencies into four domains: natural disasters (ND), accident disasters (AD), public health incidents (PHI), and social safety incidents (SSI), based on their mechanisms and nature. Each domain has distinct data characteristics and requirements, demanding models capable of processing diverse and complex data.

For data classification on social media, Unsupervised Domain Adaptation (UDA) techniques (Ben-David, Blitzer, Crammer, Kulesza, Pereira et al., 2010; Ben-David, Blitzer, Crammer, & Pereira, 2006; Ganin & Lempitsky, 2015) are crucial for transferring knowledge from a labeled source domain to an unlabeled target domain, thereby improving classification performance. Existing UDA approaches, such as statistical alignment (Li, Swersky, & Zemel, 2015; Pan, Tsang, Kwok, & Yang, 2010; Yan et al., 2017), adversarial learning (Ganin et al., 2016), generative adversarial networks (Liu & Tuzel, 2016), integrated methods (Hoffman et al., 2018; Yang, Liu, Xu, & Huang, 2023), and large language models (Lu, Luu, & Buehler, 2025; Yu, Gong, Zhou, Fang, & Zhang, 2025), have demonstrated promising results. For instance, Alam, Joty, and Imran (2018) improved feature alignment by combining labeled source domain data with unlabeled target domain data within an adversarial learning framework. Lu, Zhou, Qi, and Liu (2019) addressed information density challenges in emergency events using clustering algorithms. Li and Caragea (2020) proposed the Domain Reconstruction Classification Network (DRCN), which mitigates covariate shift through autoencoders. Ghosh, Maji, and Desarkar (2022) introduced the Global and Local Graph Neural Network (GLEN), utilizing a two-stage graph neural network to extract global information while preserving instance-level semantic features, thus enhancing the accuracy and robustness of emergency event classification. The large language model LLaMA (Dubey et al., 2024; Ye, Gan, Huang, Ge, & Tang, 2025) improved domain adaptation by learning universal representations, making it effective for UDA tasks involving diverse data distributions. CADNN (Qu & Lyu, 2025) combined adversarial domain adaptation with cross-domain sample interpolation to improve feature alignment and generalization in emergency event classification across diverse domains.

When applying UDA to emergency event classification on social media, it opens two challenging problems. First, public emergency domains (i.e., ND, AD, PHI, and SSI) exhibit distinct data characteristics and requirements, necessitating models capable of processing diverse and complex datasets. While existing studies (Alam, Joty, & Imran, 2018; Ghosh et al., 2022; Li & Caragea, 2020; Lu et al., 2019) have achieved notable success in emergency event classification within the ND domain, they are less effective for transferring knowledge across different emergency domains, as the textual variations between domains are often more pronounced than those within a single domain (Mehta, Islam, Rangwala, & Ramakrishnan, 2019). Second, domain shifts pose a significant challenge in cross-domain model training for emergency data. Different types of emergencies exhibit substantial variations in domain distribution patterns, linguistic characteristics, and emotional expressions (See Section 3). These inconsistencies hinder model adaptability across domains (Li, Yu, Du, Zhu, & Shen, 2024). Therefore, it is crucial to develop effective approaches to address domain shift while simultaneously enhancing model generalization across multiple domains for practical applications.

To address these challenges, we propose Multi-View Adversarial Neural Networks for Robust Unsupervised Domain Adaptation (MARDA), a novel UDA framework designed for application across multiple public emergency domains. MARDA integrates adversarial domain adaptation with multi-view feature learning, offering generalization and effectiveness in handling diverse, multi-domain emergency events. First, considering that the distributions of linguistic features and emotional expressions vary significantly across different domains, a cross-view processor is introduced, composed of a semantic processor, an emotional processor, and interactive cross-view integrators. The semantic and emotional processors independently extract features specific to their respective views, while the integrators capture the interactions between these views. This architecture generates comprehensive and interactive feature representations by leveraging multi-view relationships, effectively facilitating the modeling of domain discrepancies (Hassani & Khasahmadi, 2020; Li et al., 2022; Zhu et al., 2022). Second, an adaptive weighted domain enhancer is proposed to dynamically balance the contributions of different view representations. By aligning shared structures within the feature space, this module bridges gaps in cross-domain discriminative features, thereby enhancing the model's adaptability to diverse domains. Third, to further minimize distributional discrepancies across domains, an adversarial cross-view optimizer is introduced. This component employs a minimax game strategy alongside feature consistency regularization for adversarial training, effectively mitigating the influence of domain-specific features and improving cross-domain generalization. Experimental results validate MARDA's effectiveness, demonstrating superior performance compared to advanced methods across multiple open-source emergency event datasets. Notably, MARDA achieves the highest F1-Scores of 0.6757, 0.8985, 0.6703, and 0.8802 across four cross-domain tasks, establishing new benchmarks in the field of UDA for emergency scenarios. MARDA outperforms traditional models, achieving performance gains nearly 1.8 times greater than those of conventional domain adaptation approaches. This 1.8-fold improvement highlights the effectiveness of MARDA's innovative architecture in seamlessly integrating multi-view features and effectively mitigating cross-domain discrepancies.

To the best of our knowledge, this work is the first to integrate adversarial domain adaptation with multi-view feature learning specifically for unsupervised cross-domain emergency event classification. Our main contributions are summarized as follows:

- A comprehensive investigation is conducted into cross-domain emergency classification by formulating a tripartite analytical framework encompassing distribution patterns, linguistic characteristics, and emotional expressions, thereby uncovering fundamental domain discrepancies that impede effective knowledge transfer.

- MARDA is introduced as a novel UDA framework that integrates adversarial learning with multi-view representation learning. A cross-view processor is designed to combine semantic and emotional views via interactive layers, enriching cross-domain representations.
- An adaptive weighted domain enhancer is developed with a learnable weighting mechanism to enable fine-grained domain alignment across multiple views. In addition, an adversarial cross-view optimizer is incorporated to jointly enforce view and domain consistency, thereby enhancing model generalization in unseen domains.
- Extensive experiments on benchmark datasets demonstrate the effectiveness of MARDA, achieving an average F1-score improvement of 7.39% over state-of-the-art baselines. Ablation studies further verify the necessity of each component, with performance drops of 16.14% and 7.91% observed when the semantic and emotional processors are disabled, respectively.

The rest of our paper is organized as follows: Section 2 discusses the related work. Section 3 analyzed the issue of domain shift in emergency events. Section 4 describes the construction of our model. Section 5 presents the experiments, Section 6 explores theoretical and practical implications, and Section 7 summarizes our work.

2. Related work

2.1. Unsupervised domain adaptation

UDA offers an effective framework for utilizing labeled data from related domains to enhance performance on target tasks. This section reviews key research directions in UDA, including statistical methods, adversarial learning, generative adversarial methods, and their hybrid strategies. We briefly introduce the core concepts and applications of these approaches in UDA.

In statistical methods, Maximum Mean Discrepancy (MMD) (Li et al., 2015; Pan et al., 2010; Yan et al., 2017) is a commonly employed metric to assess the variance in representations between domains in Reproducing Kernel Hilbert Space (RKHS). Pan et al. (2010) were the first to introduce MMD for domain adaptation, and Li et al. (2015) further utilized MMD to align first-order statistical features between domains. Long, Cao, Wang, and Jordan (2015) proposed Multiple Kernel MMD (MK-MMD), enhancing the flexibility of feature alignment by integrating multiple kernel functions into neural networks. Long, Zhu, Wang, and Jordan (2017) further proposed a unified MMD framework aiming to align the joint distribution between the source and target domains, thereby facilitating knowledge transfer. Compared to MMD, Deep CORAL, proposed by Sun and Saenko (2016), aligns features using covariance matrices, capturing more complex relationships between domains. High-Order Moment Matching (HoMM), introduced by Chen et al. (2020), aligns third- and fourth-order statistics to achieve finer-grained feature alignment, improving domain adaptation performance. Additionally, the Contrastive Conditional Distribution (CCD) method proposed by Ragab et al. (2022) is based on MMD but focuses more on conditional probability distribution, reducing intra-class variance and maximizing inter-class boundaries by incorporating label information.

Adversarial learning techniques incorporate a domain discriminator, sometimes referred to as a domain classifier, drawing on ideas from Generative Adversarial Networks (GANs) (Goodfellow et al., 2014). The domain discriminator's task is to distinguish between source and target samples, while the feature generator attempts to generate domain-invariant features that confuse the domain discriminator. This adversarial game allows the model to learn more generalizable features. The most representative model is the Domain-Adversarial Neural Network (DANN) proposed by Ganin et al. (2016), which employs a gradient reversal layer to achieve adversarial learning, effectively reducing domain discrepancies. Pei, Cao, Long, and Wang (2018) built on DANN by proposing Multi-Adversarial Domain Adaptation (MADA), introducing multiple domain discriminators to capture complex multi-modal structures, enhancing the precision of alignment. Moreover, Long, Cao, Wang, and Jordan (2018) proposed the Conditional Domain Adversarial Network (CDAN), and Chen, Wang, Long, and Wang (2019) introduced the Batch Spectral Penalization (BSP) method, both of which improve adversarial learning by incorporating class information and optimizing feature discriminability. Xie, Zheng, Chen, and Chen (2018) proposed the MSTN method, which achieves class-level alignment by computing centroids of source samples and pseudo-labeled target samples, thereby enhancing the model's performance in the target domain.

Generative adversarial methods align the source and target domains by generating samples through GANs. CoGAN (Liu & Tuzel, 2016) adopted dual GANs, utilizing shared generators and discriminators to simultaneously model both the source and target domains, achieving generative alignment across domains. SimGAN (Shrivastava et al., 2017) enhanced the realism of synthetic data through adversarial training, making it more representative in the target domain. CycleGAN (Zhu, Park, Isola, & Efros, 2017) introduced cycle-consistency loss, ensuring consistency in domain translations without paired samples, thereby achieving effective image-to-image translation. PAT (Shi, Zhu, & Li, 2022) improved model generalization in the target domain by generating adversarial samples to augment the training data. These methods model and align distribution differences between the source and target domains at the data level through adversarial generative strategies.

Recently, many studies have attempted to integrate multiple domain adaptation methods to fully exploit their advantages. For instance, the CyCADA model proposed by Hoffman et al. (2018) combines domain mapping techniques with domain-invariant feature learning, allowing for joint training, which significantly improves domain adaptation performance. Following the introduction of Adaptive Batch Normalization (AdaBN) methods, many researchers began exploring domain-specific batch normalization strategies, as seen in the work of Chang, You, Seo, Kwak, and Han (2019) and Li, Wang, Shi, Liu, and Hou (2016). Kumar et al. (2018) proposed the Collaborative Regularization Domain Alignment (Co-DA) method, which independently learns two adversarial domain-invariant feature networks in different feature spaces, combining the ideas of ensemble learning. The Maximum Classifier Discrepancy (MCD) method proposed by Saito, Watanabe, Ushiku, and Harada (2018) organically integrates adversarial learning, ensemble methods, and target-domain discriminative feature learning, achieving more robust domain adaptation. Pei, Men, Liu, Zhuang, and Chen (2024) proposed the Evidential Aggregation and Adaptation Framework (EAAF) for Multi-Source-Free UDA. By introducing evidential prediction uncertainty and evidential adjacency-consistent uncertainty, EAAF enhances instance-level aggregation and ensures robust adaptation to the target domain. With the development of Transformer models, the TVT (Yang et al., 2023) model enhances feature transferability and discriminability by introducing an adaptation module, leveraging the powerful modeling capabilities of transformers to improve performance in cross-domain tasks. The CdTrans model (Xu et al., 2021) utilizes the robustness of cross-attention mechanisms, focusing on directly aligning features between different domains, capturing and aligning data distributions between the source and target domains through a cross-domain transformer architecture, thus improving domain adaptation performance.

Despite significant progress in UDA research, existing methods often struggle with the diversity and uncertainty of cross-domain features in the context of emergency event classification (Pei et al., 2024; Westfechtel, Yeh, Zhang, & Harada, 2024). Our MARDA overcomes these challenges by integrating multi-view feature fusion with semantic and emotional insights, alongside adversarial training. This approach improves the capture of cross-domain shared features and enables the classifier to learn more flexible decision boundaries, leading to enhanced performance in emergency event classification across diverse domains.

2.2. UDA for emergency events

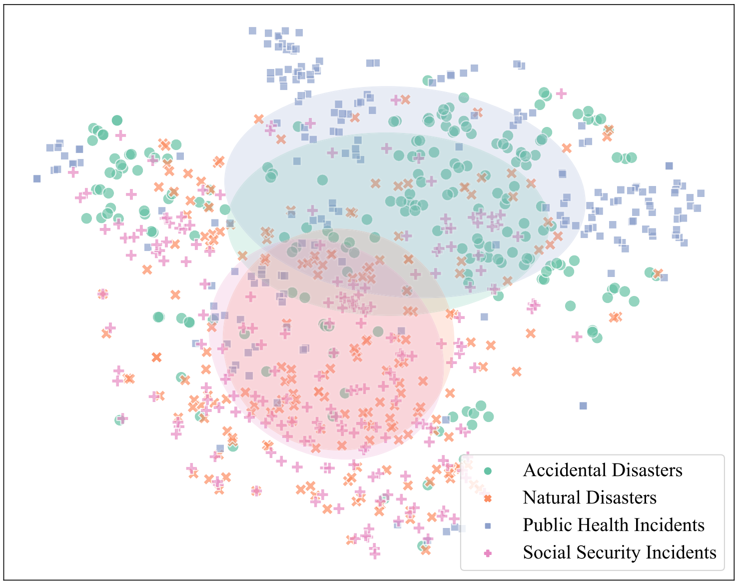
Emergency event classification is a crucial area of research, yet it faces numerous challenges such as the scarcity of labeled datasets, data transferability, diversity, and imbalance. The scarcity issue makes it difficult for models to generalize and adapt effectively during training, while data transferability involves significant distribution differences between regions and cultural contexts, making it challenging for traditional classification methods to cope effectively. Moreover, data diversity reflects the wide range of emergency event types, each with its unique characteristics. The imbalance issue is particularly evident in social media data, where the frequent occurrence of certain event types may cause models to develop biases in classification, thereby affecting overall accuracy and robustness.

In the field of emergency event data analysis, several innovative methods have been proposed to address these challenges. First, Alam, Joty, and Imran (2018) introduced an adversarial learning method, proposing an end-to-end domain adaptation framework. This framework combines labeled and unlabeled data from the source domain and unlabeled data from the target domain, achieving feature alignment through a gradient reversal layer and a graph convolutional network. This method demonstrates excellent cross-domain adaptability and generalization on datasets from the 2015 Nepal earthquake and the 2013 Queensland floods. Subsequently, Lu et al. (2019) proposed a clustering algorithm-based data processing method to address the information density issue in tweets related to emergency events. They track and characterize the evolution of rare events in the real world by analyzing social media interactions, validating the method on the 2012 Hurricane Sandy dataset. This method constructs an automated system for processing and classifying emergency event information by identifying and categorizing different types of tweets through clustering analysis. Building on this, Li and Caragea (2020) proposed the Domain Reconstruction Classification Network (DRCN), a framework that reduces covariate shift by reconstructing target domain data through an autoencoder. This LSTM-based autoencoder structure, independent of token-level information, can reconstruct the semantic features of the source domain in the target domain and has demonstrated strong cross-domain data processing capabilities on multiple natural emergency event datasets. Ghosh et al. (2022) proposed the Global and Local Graph Neural Network (GLEN) method to address cross-domain challenges in emergency event classification. Their approach extracts global information and retains instance-level semantic features through a two-stage graph neural network structure, significantly enhancing the accuracy and robustness of emergency event classification by utilizing a large amount of unlabeled data from the source domain. Validation on multiple emergency event datasets has shown that this method has good cross-domain transferability. Additionally, Qu and Lyu (2025) proposed the Class-Imbalanced Adversarial Neural Network (CADNN) to tackle UDA challenges in emergency event classification. CADNN combines adversarial domain adaptation with a novel cross-domain interpolation strategy that generates aligned sample pairs while preserving the original data distribution through centroid preservation. By integrating this interpolation within the adversarial training framework, CADNN optimizes a joint loss function to improve generalization and effectively handle class imbalance.

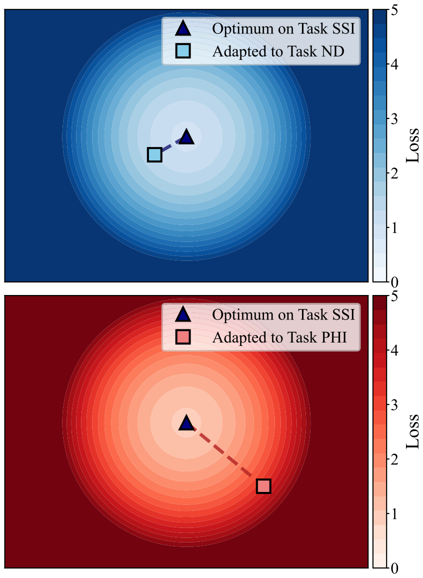
While these methods have demonstrated effectiveness in classifying emergency events within the ND domain, they encounter significant challenges when applied to more complex event categories such as AD, PHI, and SSI. This is primarily due to the intricate semantic structures and the pronounced domain disparities, which hinder their ability to generalize and transfer knowledge across different domains effectively (Ghosh et al., 2022; Qu & Lyu, 2025). Our research aims to extend event transfer across a broader range of emergency events (including AD, ND, PHI, and SSI) to address these more complex and diverse classification challenges.

3. Domain transfer analysis

To improve model performance in domain transfer tasks, this section presents a thorough analysis of domain distribution patterns, linguistic choices, and emotional expressions across domains. By examining domain distribution patterns, a deeper understanding of the differences between source and target domains is gained. The analyses in Sections 3.2 and 3.3 reveal variations in linguistic and emotional expressions across domains, providing valuable insights that inform the development of robust adaptation strategies.



(a) Feature distribution with t-SNE



(b) Transfer loss comparison

Fig. 1. Visualization of domain distribution patterns.

3.1. Domain distribution patterns

To examine domain adaptation characteristics in emergency events, we visualize the feature distributions of AD, ND, PHI, and SSI using t-SNE, and select a subset of samples from the test set in each category to ensure the visualization captures the overall feature space of the four domains. As shown in Fig. 1(a), certain domain pairs, such as AD–PHI and ND–SSI, exhibit notable overlap, indicating similarity in feature representation and a high potential for knowledge transfer. In contrast, pairs such as AD–ND and PHI–SSI show clear separation, suggesting substantial distributional differences that may require domain-specific adaptation strategies.

To quantitatively validate the transfer potential suggested by the visualization, we conduct experiments using the widely adopted NLP model RoBERTa (Cui et al., 2020; Cui, Che, Liu, Qin, & Yang, 2021). The model is trained on SSI and evaluated when adapted to Task ND and Task PHI. As shown in Fig. 1(b), adaptation from SSI to ND yields lower loss, corroborating the t-SNE-based observation of higher transferability, whereas adaptation to PHI results in higher loss, indicating weaker transferability. These results confirm that while certain domain pairs share similar feature spaces conducive to transfer, others require tailored adaptation strategies to bridge substantial representational gaps.

3.2. Linguistic choice

To illustrate domain-specific vocabulary usage, we create word clouds representing word frequency across different domains, as shown in Fig. 2. By comparing word clouds from four domains, we observe each domain's unique characteristics and key semantic differences. For instance, the word cloud for the AD domain includes vocabulary related to accidents caused by human error or technical failures, such as “helicopter crash” and “factory explosion”, indicating the suddenness and high risk associated with these events. The word cloud for the ND domain features vocabulary focuses on natural calamities, such as “Hurricane Sandy”, reflecting the environmental and geographical context of such events. The PHI domain's word cloud features terms related to global infectious disease outbreaks, such as “Ebola” and “MERS”, highlighting medical terminology and control strategies. Similarly, the word cloud for the SSI domain focuses on events like the “Boston Marathon Bombing”, covering issues related to terrorism and public safety. These semantic and contextual differences pose significant challenges for models during cross-domain transfer, particularly when adapting from one specific domain to another, as they must adapt to entirely different contexts and knowledge domains.

3.3. Emotional expression

In the analysis of emotional distribution, we explore the emotions associated with events across different domains in both informative and uninformative texts. By normalizing the values of the same emotional features in uninformative and informative texts and visualizing these distributions in Fig. 3, two key findings are revealed.

First, the same emotion manifests differently across various event types, with emotional intensity varying from one event to another. For example, “Anger” is more prevalent in AD, while “surprise” is more prominent in PHI. “Sadness” primarily appears

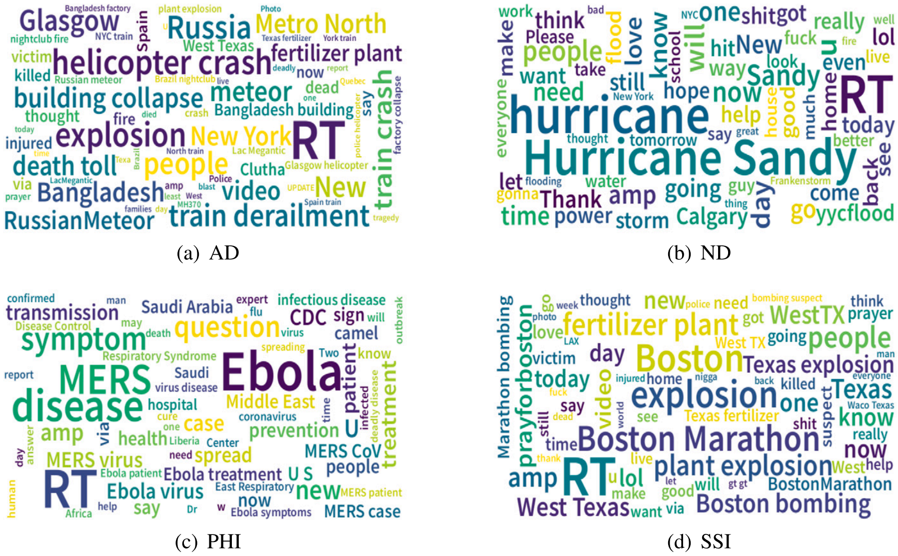


Fig. 2. Word clouds for different emergency events.

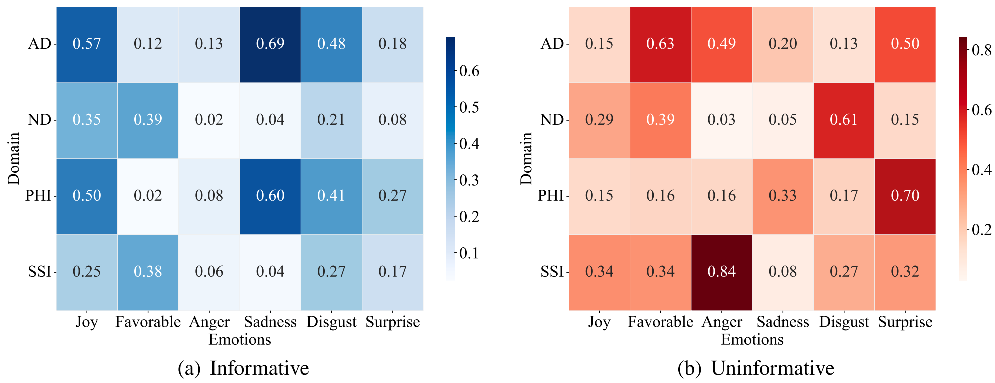


Fig. 3. Heatmaps of emotions for different emergency events.

in AD and PHI, leading to higher emotional intensity in these two event types, indicating that these events exhibit a greater emotional concentration. Second, the emotional distribution in uninformative texts tends to be more extreme, while informative texts show a more balanced distribution. In SSI, uninformative texts show significantly higher “Anger” than other event types, while in informative texts, “Anger” is more evenly distributed. Uninformative texts also exhibit heightened “Anger” and “Surprise” in both SSI and PHI, whereas informative texts have a more balanced emotional distribution with lower intensity overall.

4. Methodology

In this section, we introduce MARDA, an innovative framework for assessing the validity of emergency event information through UDA. It begins with the problem definition, followed by a detailed description of its components. An overview of mathematical symbols and their definitions is provided in Table 2.

Fig. 4 illustrates the overall architecture of MARDA, which follows a structured pipeline for UDA in multi-domain emergency event classification. The process begins with a dual-view encoding stage, where the semantic and emotional processors independently extract discriminative representations from linguistic and affective inputs. These heterogeneous features are fused through interactive cross-view integrators that capture inter-view dependencies to enhance representational expressiveness. The resulting joint representations are then refined by an adaptive weighted domain enhancer, which employs a learnable view-weighting mechanism that dynamically calibrates the contributions of each view and facilitates fine-grained structural alignment across domains. To mitigate residual domain discrepancies, an adversarial cross-view optimizer enforces domain and view consistency via a minimax training objective and feature consistency regularization. Finally, the unified and domain-agnostic representations are passed to the emergency event predictor for robust downstream classification.

Table 1
Detailed emergency events listing.

Categories	Emergency events
Accidental Disasters	Venezuela Refinery Explosion, Bangladesh Savar Building Collapse Brazil Nightclub Fire, Canada Lac-Megantic Train Crash Glasgow Helicopter Crash, New York Train Crash Russia Meteor Incident, Spain Train Crash West Texas Explosion, Malaysia Airlines Incident
Natural Disasters	Colorado Wildfires, Costa Rica Earthquake, Guatemala Earthquake Italy Earthquakes, Philippines Floods, Typhoon Pablo Hurricane Sandy, Alberta Floods, Australia Bushfires Bohol Earthquake, Colorado Floods, Italy Sardinia Floods Manila Floods, Oklahoma Tornado, Typhoon Yolanda Queensland Floods, Singapore Haze, Pakistan Earthquake California Earthquake, Chile Earthquake, Iceland Volcano India Floods, Mexico Hurricane Odile, Pakistan Floods Philippines Typhoon, Typhoon Hagupit, Worldwide Landslides Nepal Earthquake, Vanuatu Cyclone
Public Health Incidents	Middle East Respiratory Syndrome, Worldwide Ebola Outbreak
Social Security Incidents	Boston Marathon Bombings, Los Angeles Airport Shootings West Texas Explosion

Table 2
Mathematical symbols and descriptions.

Symbol	Description	Symbol	Description
General Setup			
I_i^S, y_i^S	Source sample and label	I_i^T	Target sample
N_S, N_T	Number of source/target samples	y_i^d	Ground-truth label
$f(I^S;\theta)$	Classification model	θ	Classification model parameters
Feature Extraction			
E_{sem}, E_{emo}	Semantic/Emotional embeddings	P_{sem}, P_{emo}	Semantic/Emotional processors
H_{sem}, H_{sem}^{pert}	Original/Perturbed semantic representation	H_{emo}, H_{emo}^{pert}	Original/Perturbed emotional representation
δ_{sem}, δ_{emo}	Semantic/Emotional perturbation		
Cross-View Integration			
w_i^{sem}, w_j^{emo}	Weights of semantic/emotional views	n_{sem}, n_{emo}	Number of semantic/emotional views
H_{mix}, H_{mix}^{pert}	Original/Perturbed interactive representation	H_{multi}, H_{multi}^{pert}	Original/Perturbed cross-view representation
H_{int}	Enhanced cross-view representation	$Integrate(\cdot)$	Feature integration function
Z	Number of cross-view heads	R	Combined domain representation
$h(\cdot)$	Weight adaptive function	H'	Adaptive weight vector
H_{all}	Final aggregated feature		
Prediction			
$\mathcal{L}_{class}$	Classification loss	λ	Regularization coefficient

4.1. Research objectives

MARDA's primary objective is to develop a robust UDA framework for emergency event detection that effectively transfers knowledge from a labeled source domain to an unlabeled target domain. To this end, MARDA focuses on the following key goals:

1. **Model Adaptation and Generalization:** The goal is to design a classification model $f(I^S;\theta)$ with parameters θ that is trained on labeled data from the source domain S (i.e., $\{(I_i^S, y_i^S)\}_{i=1}^{N_S}$) and generalizes effectively to the target domain T, where only unlabeled data $\{I_i^T\}_{i=1}^{N_T}$ is available.
2. **Mitigating Domain Shift:** A core challenge in this work is reducing the domain shift between S and T. This involves developing techniques to align the feature distributions across domains, thereby ensuring that the model maintains robust performance in diverse emergency event scenarios despite the absence of target domain labels.
3. **Accurate Event Classification:** In the dataset, each piece of information I_i^d (with $d \in \{S,T\}$) is assigned a binary label $y_i^d \in \{0,1\}$, where

$$y_i^d = \begin{cases} 1, & \text{if the information is uninformative,} \\ 0, & \text{if the information is informative.} \end{cases}$$

   The objective is to accurately classify these events in both domains, ensuring that informative and uninformative events are correctly identified, even when the target domain lacks labeled samples.

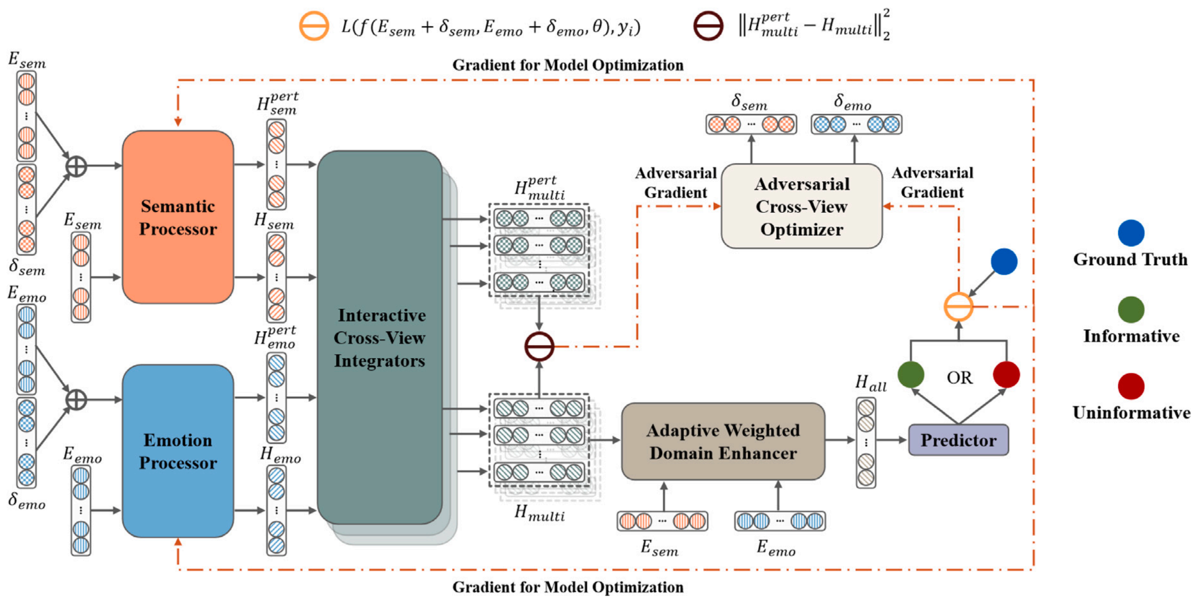


Fig. 4. The framework of MARDA.

4.2. Cross-view processor

Based on the analysis of domain distribution patterns, linguistic choice, and emotional expression across domains in Section 3.1, a cross-view processor is designed to comprehensively capture the multi-dimensional feature representations of information. Specifically, the framework consists of a semantic processor (SemPro) and an emotional processor (EmoPro), which model information from semantic and emotional perspectives, respectively. MARDA further integrates SemPro and EmoPro to obtain interactive features across multiple views, helping to address feature differences between domains and improve the model's performance in the UDA task.

4.2.1. Semantic processor

Suppose an emergency event text I consists of M tokens. Each token $m \in \{1, 2, \dots, M\}$ is encoded as an embedding vector e_m^{sem} by the RoBERTa pre-trained model (Cui et al., 2020, 2021). The SemPro aims to extract effective semantic representations from the text. In this work, TextCNN (Rakhlin, 2016) is employed as SemPro, using convolutional kernels of different window sizes to capture local semantic features. The final output representation of SemPro is:

$$H_{sem} = P_{sem}(E_{sem}) = P_{sem}(\{e_1^{sem}, e_2^{sem}, \dots, e_M^{sem}\}), \tag{1}$$

where $E_{sem} = \{e_1^{sem}, e_2^{sem}, \dots, e_M^{sem}\}$ represents the embedding vectors of each token in the text, and $P_{sem}(\cdot)$ denotes the TextCNN model.

To enhance the model's generalization ability and adversarial robustness, a trainable adversarial perturbation δ_{sem} is introduced, which is applied to the semantic embeddings. This perturbation leverages the redundancy and complementarity of semantic information, ensuring that the model maintains stable performance even under input perturbations. The adversarial semantic representation is formulated as:

$$H_{sem}^{pert} = P_{sem}(E_{sem} + \delta_{sem}) = P_{sem}(\{e_1^{sem} + \delta_1^{sem}, e_2^{sem} + \delta_2^{sem}, \dots, e_M^{sem} + \delta_M^{sem}\}), \tag{2}$$

where $\delta_{sem} = \{\delta_1^{sem}, \delta_2^{sem}, \dots, \delta_M^{sem}\}$ denotes the adversarial perturbations added to the corresponding semantic embeddings.

4.2.2. Emotional processor

The EmoPro is primarily responsible for extracting and integrating various emotional features from the text. These features are combined to capture the complex emotional information in the text. Each emotional feature is represented as an emotional vector. Specifically, MARDA refers to the emotional feature extraction method proposed by Zhang et al. (2021) to extract the emotional polarity feature ζ_{pol}, emotional lexicon feature ζ_{lex}, emotional intensity feature ζ_{int}, and other auxiliary features ζ_{aux} from the text, as detailed in Table 3. These features are concatenated to form the final comprehensive emotional representation:

$$U = \zeta_{pol} \oplus \zeta_{lex} \oplus \zeta_{int} \oplus \zeta_{aux} = \{e_1^{emo}, e_2^{emo}, \dots, e_C^{emo}\}, \tag{3}$$

Table 3
Emotion feature descriptions and symbols.

Emotion feature	Symbol	Detailed description
Emotion polarity	ζ_{pol}	Use a publicly available emotion classifier to obtain fine-grained emotion probabilities, and combine them with an emotion lexicon to calculate coarse-grained emotion scores.
Emotion lexicon	ζ_{lex}	Calculate the score of each word and its context under different emotions, and summarize the overall emotion score.
Emotion intensity	ζ_{int}	Calculate the intensity-weighted score of each word, and summarize these scores to generate an overall emotional intensity feature vector.
Auxiliary features	ζ_{aux}	Capture emotion signals conveyed by emojis and punctuation marks, and add the frequency of emotional words and personal pronouns.

where U represents the concatenated emotional features, and e_c^{emo} is the cth emotional vector. Finally, EmoPro processes these comprehensive emotional vectors through a multilayer perceptron (MLP), and its output representation is:

$$H_{emo} = P_{emo}(E_{emo}) = P_{emo}(\{e_1^{emo}, e_2^{emo}, \dots, e_C^{emo}\}), \tag{4}$$

where $E_{emo} = \{e_1^{emo}, e_2^{emo}, \dots, e_C^{emo}\}$ represents the extracted emotional features from the text.

Similarly, a trainable adversarial perturbation δ_{emo} is introduced to the emotional embeddings. The adversarial emotional representation is formulated as:

$$H_{emo}^{pert} = P_{emo}(E_{emo} + \delta_{emo}) = P_{emo}(\{e_1^{emo} + \delta_1^{emo}, e_2^{emo} + \delta_2^{emo}, \dots, e_C^{emo} + \delta_C^{emo}\}), \tag{5}$$

where $\delta_{emo} = \{\delta_1^{emo}, \delta_2^{emo}, \dots, \delta_C^{emo}\}$ denotes the adversarial perturbations added to the corresponding emotional embeddings.

4.2.3. Interactive cross-view integrators

Drawing inspiration from multi-channel CNNs (He, Zhang, Ren, & Sun, 2016; Huang, Liu, Van Der Maaten, & Weinberger, 2017; Tao et al., 2019; Vaswani et al., 2017; Zhu et al., 2022, 2019), a multi-channel architecture is proposed for the extraction of rich features from both semantic and emotional perspectives of emergency events. Each network utilizes a multi-channel structure to represent input data from different perspectives, enabling the model to capture diverse patterns and enhance its ability to process emergency event information. Given that different domains require varying levels of semantic and emotional information, a single cross-view representation may not meet the requirements of all domains (Huang et al., 2025; Zhu et al., 2022). For instance, the PHI domain may rely more heavily on semantic information, whereas the AD domain may require more emotional information. Thus, MARDA separately extracts n_{sem} semantic networks and n_{emo} emotional network representations to provide a robust foundation for subsequent cross-view interactions.

To more effectively integrate these multi-view features, an interactive cross-view integrator is designed. This interaction mechanism aims to capture interrelationships between views and generate combined representations with higher expressiveness. Rather than directly enumerating all possible view combinations, our interaction mechanism adaptively learns the relative importance of each view (e.g., the semantic view weight w_i^{sem} and the emotional view weight w_i^{emo}), maintaining computational efficiency while mitigating the negative impact of noisy views on model performance.

Specifically, by applying weighted operations on each view's features, MARDA integrates information from different views to obtain a comprehensive interactive feature representation, denoted by H_{mix}:

$$H_{mix} = \exp\left[\sum_{i=1}^{n_{sem}} w_i^{sem} \ln H_i^{sem} + \sum_{j=1}^{n_{emo}} w_j^{emo} \ln H_j^{emo}\right], \tag{6}$$

where w_i^{sem} and w_j^{emo} represent the importance of the semantic and emotional views, respectively, which are learnable parameters.

Additionally, this cross-view fused feature representation can also be achieved through product operations between views, further enhancing the ability to integrate information:

$$H_{mix} = \prod_{i=1}^{n_{sem}} (H_i^{sem})^{w_i^{sem}} \odot \prod_{j=1}^{n_{emo}} (H_j^{emo})^{w_j^{emo}}. \tag{7}$$

To further enhance robustness, the adversarial perturbation mechanism is extended to cross-view representations within MARDA. Following the same fusion strategy, MARDA aggregates the adversarially perturbed semantic and emotional features to construct the adversarial cross-view representation H_{mix}^{pert}:

$$H_{mix}^{pert} = \prod_{i=1}^{n_{sem}} (\{H_{sem}^{pert}\}_i)^{w_i^{sem}} \odot \prod_{j=1}^{n_{emo}} (\{H_{emo}^{pert}\}_j)^{w_j^{emo}}. \tag{8}$$

However, a single cross-view representation may not satisfy the needs of all domains. Different emergency event domains may require distinct cross-view combinations. Therefore, interactive cross-view integrators are designed with Z heads, where each head independently learns and generates a cross-view representation to meet the diverse requirements of different domains. Finally, MARDA obtains Z cross-view representations $H_{multi} = \{H_{mix}^z\}_{z=1}^Z$ and $H_{multi}^{pert} = \{\{H_{mix}^{pert}\}^z\}_{z=1}^Z$, where Z is the number of cross-view combinations. These representations collectively enhance the model's effectiveness in transfer learning across various emergency event domains. This mechanism dynamically adjusts the weights and interactions of the views to better adapt to the classification tasks and feature requirements of different domains, allowing the model to extract and utilize the most relevant information for each domain.

4.3. Adaptive weighted domain enhancer

In this section, an adaptive weighted domain enhancer is proposed to enhance adversarially augmented cross-view features. First, MARDA combines the adversarially augmented cross-view features, event text embeddings E_{sem}, and emotional features E_{emo} through a feature integration operation to construct an enhanced feature representation H_{int}^{z}:

$$H_{int}^{z} = Integrate(H_{multi}, [E_{sem}, E_{emo}]), \forall z \in \{1, 2, \dots, Z\}, \tag{9}$$

where $Integrate(\cdot)$ denotes the feature integration operation that combines the adversarially augmented cross-view features, E_{sem}, and E_{emo}. Integrating these features forms a more comprehensive feature representation H_{int}, encompassing both the semantic and emotional content of the information as well as features enhanced through adversarial training. This approach fully leverages the advantages of each view. Further integration produces the rich domain representation $R = [H_{int}, E_{sem}, E_{emo}]$ provided by the feature enhancer.

To further optimize the expressive capacity of the integrated features, an adaptive weighting mechanism is applied:

$$H' = \mathrm{softmax}(h(R)), \tag{10}$$

where $h(R)$ is a function that maps the integrated features R to a weight vector, and the softmax operation normalizes the weights. The adaptive weights dynamically adjust the importance of each view's features in the final aggregation. The final aggregated feature H_{all} is obtained by weighted summation of all view features H_{int}, where Z denotes the total number of views:

$$H_{all} = \sum_{z=1}^{Z} H' H_{int}^{z}. \tag{11}$$

By integrating adversarially enhanced features, semantic features, and emotional features, a diverse and robust feature space is created within MARDA, effectively handling uncertainties and domain differences. The adaptive weighting mechanism optimizes this feature space by dynamically adjusting the importance of each view's features, thereby improving the model's ability to capture key information and enhance validity detection accuracy. This fusion not only improves the model's generalization ability but also facilitates effective adaptation to shared feature representations during domain transfer.

4.4. Adversarial cross-view optimizer

To enhance the model's robustness in transfer learning for emergency event information validity, an adversarial cross-view optimizer is proposed using adversarial training. Unlike traditional adversarial training methods, this approach applies adversarial perturbations to cross-view features instead of individual word vectors. This design aims to fully leverage the redundancy and complementarity of cross-view information, thereby enhancing the model's robustness against input perturbations. The objective function is designed as follows:

$$\begin{aligned} &\min_{\theta} \mathbb{E}_{(E_{sem},E_{emo},y_i)\sim\mathcal{D}} \left[\max_{\delta_{sem},\delta_{emo}} \left[\mathcal{L}_{class} \left(f\left(E_{sem} + \delta_{sem}, E_{emo} + \delta_{emo}, \theta \right), y_i \right) + \lambda \| H_{multi}^{pert} - H_{multi} \|_2^2 \right] \right] \\ &\text{s.t. } \|\delta_{sem}\|_p \le \epsilon_{sem}, \quad \|\delta_{emo}\|_p \le \epsilon_{emo}, \end{aligned} \tag{12}$$

where $\mathcal{L}_{class}$ is the loss function used to quantify the model's prediction error under the given perturbations. δ_{sem} and δ_{emo} represent the adversarial perturbations applied to the semantic features and emotional features, respectively. ϵ_{sem} and ϵ_{emo} define the maximum norms of these perturbations, θ represents the overall parameters of the model, and λ is the coefficient. To manage the impact of perturbations on the combined features, a regularization term, $\lambda \| H_{multi}^{pert} - H_{mix} \|_2^2$, is included in the objective function, where H_{multi}^{pert} denotes the perturbed mixed features. This feature alignment approach helps stabilize the feature space and prevents adversarial perturbations from excessively deviating the feature representation from its original distribution.

In adversarial training, the generation of adversarial perturbations δ_{sem} and δ_{emo} is typically achieved by maximizing the model's loss under these perturbations. However, due to the presence of the regularization term, simultaneously optimizing both perturbation variables can be complex (Chen, Sun, & Yin, 2021; Huh, Cheung, Agrawal, & Isola, 2023; Zhang, Yoon, Bansal, & Yao, 2024). To address this challenge, MARDA adopts an alternating optimization strategy, where MARDA optimizes the semantic and emotional perturbations in turn, while keeping one perturbation fixed.

First, while keeping the emotional perturbation δ_{emo} fixed, the semantic perturbation δ_{sem} is optimized:

$$\delta_{sem}^{*} = \arg \max_{\|\delta_{sem}\|_p \le \epsilon_{sem}} \left[\mathcal{L}_{class} \left(f\left(E_{sem} + \delta_{sem}, E_{emo}, \theta \right), y_i \right) + \lambda \| H_{multi}^{pert}(E_{sem} + \delta_{sem}, E_{emo}) - H_{multi} \|_2^2 \right]. \tag{13}$$

Then, while keeping the semantic perturbation δ_{sem} fixed, the emotional perturbation δ_{emo} is optimized:

$$\delta_{emo}^{*} = \arg \max_{\|\delta_{emo}\|_p \le \epsilon_{emo}} \left[\mathcal{L}_{class} \left(f\left(E_{sem}, E_{emo} + \delta_{emo}, \theta \right), y_i \right) + \lambda \| H_{multi}^{pert}(E_{sem}, E_{emo} + \delta_{emo}) - H_{multi} \|_2^2 \right]. \tag{14}$$

The alternating optimization process continues until both semantic and emotional perturbations converge. The final objective of the joint optimization is:

$$\delta^*_{sem}, \delta^*_{emo} = \arg \max_{\substack{\|\delta_{sem}\|_p \le \epsilon_{sem} \\ \|\delta_{emo}\|_p \le \epsilon_{emo}}} \left[\mathcal{L}_{class} \left(f \left(E_{sem} + \delta_{sem}, E_{emo} + \delta_{emo}, \theta \right), y_i \right) + \lambda \| H^{pert}_{multi} - H_{multi} \|_2^2 \right]. \tag{15}$$

This method offers several key advantages. By applying perturbations to both semantic and emotional features, the model leverages the redundancy and complementarity of multi-view information, ensuring stable performance even in complex scenarios, such as those involving emergency event messages. The alternating optimization strategy improves computational efficiency while preserving the accuracy of perturbation application. Additionally, incorporating a regularization term based on the fused multi-view features H_{mix} constrains the impact of these perturbations on the overall feature representation, preventing excessive deviation from the original feature distribution.

4.5. Emergency event predictor

After applying the adversarial cross-view optimizer, the model feeds the fused feature representation H_{all} into a multilayer perceptron (MLP) to generate the predicted probability $\hat{p}$:

$$\hat{p} = \text{Sigmoid}(\text{MLP}(H_{all})). \tag{16}$$

To evaluate the classification performance of the model, MARDA employs the cross-entropy loss function, which measures the discrepancy between the predicted probability and the true label. The cross-entropy loss function is defined as:

$$\mathcal{L}_{class} = -y \log \hat{p} - (1 - y) \log(1 - \hat{p}), \tag{17}$$

where y is the true label and $\hat{p}$ is the predicted probability.

The complete loss function incorporates the classification loss along with the adversarial regularization term, as defined previously:

$$\mathcal{L} = \mathcal{L}_{class} + \lambda \| H^{pert}_{multi} - H_{multi} \|_2^2. \tag{18}$$

Algorithm 1 shows the detailed process of MARDA. Lines 1 and 2 generate emergency semantic information E_{sem} and emotional information E_{emo} from the dataset and initialize the model parameters. Subsequently, lines 3 to 16 perform multiple training iterations to update the model. During each training iteration, lines 6 and 7 utilize the SemPro and EmoPro modules to extract both the original and perturbed features of semantic and emotional information from the event data. Then, in lines 8 and 9, the Integrators module fuses the semantic and emotional features, producing multi-head fused features H_{multi} and perturbed multi-head fused features H^{pert}_{multi}. In lines 10 and 11, the Enhancer modules further enhance the integrated features by combining the original information E_{sem} and E_{emo} to obtain H_{int}, which is then multiplied by the adaptive weights H'. In lines 12 and 13, the Optimizer updates the perturbation variables, and gradient descent is applied to update the model parameters θ. The algorithm then computes the prediction result $\hat{y}$ and evaluates the model's performance using the loss function $\mathcal{L}$. After training, lines 17 to 21 enter the testing phase, where the algorithm computes and returns the prediction results for the test data using the trained model parameters.

5. Experiments

5.1. Emergency event datasets

Our study utilizes a comprehensive dataset designed to cover four major categories of emergency events: accidental disasters, natural disasters, public health incidents, and social security incidents. The dataset construction draws on the work of Zhang, Qian, Fang, and Xu (2020) and incorporates data from Alam, Ofli, and Imran (2018), Olteanu, Castillo, Diaz, and Vieweg (2014), Olteanu, Vieweg, and Castillo (2015), and Nguyen et al. (2020).

Specifically, the dataset contains 47 emergency events across four main categories, distributed as follows:

- AD: This category contains ten severe accidents, such as the Venezuelan Refinery Explosion and the Malaysia Airlines Incident, providing crucial data for studying disasters caused by human factors.
- ND: This is the largest category in the dataset, comprising 31 events, ranging from the Colorado Wildfires in the United States to the Nepal Earthquake. These events illustrate the widespread occurrence and impact of natural disasters across various regions.
- PHI: This category includes two global public health crises, namely the Middle East Respiratory Syndrome (MERS) and the global Ebola epidemic, highlighting the significant impact of transnational health threats.
- SSI: This category includes three events, such as the Boston Marathon Bombing and the Los Angeles Airport Shooting, reflecting the sudden and complex nature of social security issues.

Table 1 provides detailed statistics for each event category, demonstrating that the dataset not only covers a wide range of categories but also spans multiple countries and regions, reflecting the characteristics and impacts of disasters across different parts of the world. Table 4 shows the label distribution, indicating certain imbalances: ND and SSI have relatively abundant samples, whereas AD and PHI contain fewer instances. It also summarizes the presence of both informative and uninformative events across all four domains, which forms the basis for our investigation into knowledge transfer and its applications in emergency event response.

Algorithm 1 The Algorithm of MARDA.

Input: Emergency event information from the Dataset
Output: Prediction result for each piece of information

Generate E_{sem}, E_{emo} from dataset
Initialize model parameters θ, H', λ, ϵ, δ_{sem}, δ_{emo}
for each training iteration **do**
  Sample a batch of training data
  for each perturbation step **do**
    /* *Cross-View Processor* */
    $H_{sem}, H_{sem}^{pert} \leftarrow \mathrm{SemPro}(E_{sem}), \mathrm{SemPro}(E_{sem} + \delta_{sem})$ // Extract semantic features
    $H_{emo}, H_{emo}^{pert} \leftarrow \mathrm{EmoPro}(E_{emo}), \mathrm{EmoPro}(E_{emo} + \delta_{emo})$ // Extract emotional features
    /* *Interactive Cross-View Integrators* */
    $H_{multi} \leftarrow \mathrm{Integrators}(H_{sem}, H_{emo})$ // Integrate cross-view features
    $H_{multi}^{pert} \leftarrow \mathrm{Integrators}(H_{sem}^{pert}, H_{emo}^{pert})$ // Integrate perturbed cross-view features
    /* *Adaptive Weighted Domain Enhancer* */
    $H_{int} \leftarrow \mathrm{Integrate}(H_{multi}, E_{sem}, E_{emo})$
    $H_{all} \leftarrow \mathrm{Enhancer}(H_{int}, H')$ // Adapt features based on domain-specific perturbations
    /* *Adversarial Cross-View Optimizer* */
    $\delta_{review}^{*}, \delta_{emotion}^{*} \leftarrow \mathrm{Optimizer}(\hat{y}, y_{true}, H_{multi}, H_{multi}^{pert}, \delta_{sem}, \delta_{emo}, \lambda, \epsilon)$ // Update perturbation
    Update model parameters θ using gradients from $\mathcal{L}$ with Eq. (18)
    /* *Emergency Event Predictor* */
    $\hat{y} \leftarrow \mathrm{Predictor}(H_{all})$ // Compute predictions
  end for
end for
for each testing iteration **do**
  Sample a batch of testing data
  Compute and save $\hat{y}$ with trained parameters
end for
return $\hat{y}$ for all testing users

Table 4
Data statistics of emergency events.

Domain	AD	ND	PHI	SSI	All
Informative	2643	4805	1814	4819	14081
Uninformative	159	4811	183	4774	9927
Total	2802	9616	1997	9593	24 008

5.2. Experimental setup

For the experiments, the entire dataset is randomly divided into training, validation, and test sets in a 6:2:2 ratio, maintaining consistent domain distribution across each set. We use the widely adopted RoBERTa model as the text encoder, with the maximum sequence length limited to 170. The TextCNN model employs five kernels with sizes 1, 2, 3, 5, 10, and 64 channels. All experimental methods utilize the Adam optimizer (Kingma & Ba, 2014), with the initial learning rate set to 2e-5 and the batch size fixed at 8. The number of channels is tuned through a grid search between 1 and 10. To ensure fair comparisons, the hidden layer sizes for all BiGRU and BiLSTM models are set to 320. For MLP-based methods, a two-layer MLP architecture is adopted, with the hidden layer dimension also set to 320, and ReLU used as the activation function. The performance of MARDA is evaluated using common metrics, including accuracy (ACC), macro F1-Score (F1), and area under the ROC curve (AUC).

All models are trained and evaluated on the same dataset under identical conditions to ensure fair comparison. Experiments are conducted on two NVIDIA V100 GPUs (each with 32 GB memory). Each model is trained for 100 epochs, with each setting repeated 10 times, and average results reported. The total training time per run is less than one hour.

5.3. Comparison of advanced baseline models

In this section, we evaluate the effectiveness of our model by comparing it with several representative baseline models from the field of text classification. These models include traditional feature extraction methods (e.g., LDA and LIWC), traditional machine learning models (e.g., BiLSTM, BiGRU, TextCNN, RoBERTa, and BART), and domain adaptation models (e.g., EANN, DANN, DRCN, and EDDFN).

5.3.1. Advanced baseline models

Traditional feature extraction models employ hand-crafted algorithms to convert data into feature vectors using domain knowledge and predefined rules, which serve as the foundation for subsequent analysis and modeling.

- LDA (Blei, Ng, & Jordan, 2003): A generative model that represents documents as mixtures of topics, producing topic vectors used for text classification.
- LIWC (Pennebaker, 2001): A tool that categorizes words into psychological and emotional categories, generating feature vectors for sentiment analysis and other text classification tasks.

Traditional machine learning models leverage knowledge from a source domain to enhance performance in a target domain. These models assume that the source and target domains share some similarities, which allows knowledge from the source domain to be applicable to the target domain. These models are particularly useful when there is abundant labeled data in the source domain but limited labeled data in the target domain.

- BiLSTM (Graves, Fernández, & Schmidhuber, 2005): Extends Long Short-Term Memory(LSTM) by processing text sequences in both forward and backward directions, capturing dependencies from both contexts to enhance sequence modeling.
- BiGRU (Ma et al., 2016): Similar to BiLSTM, but with a simpler gating mechanism, BiGRU captures bidirectional context and long-term dependencies in text, enhancing its ability to handle complex sequences.
- TextCNN (Kim, 2014): Uses convolutional filters of various sizes to capture local features in text, excelling in sentence classification and short-text tasks through pattern extraction and pooling.
- RoBERTa (Liu, 2019): An optimized version of BERT with improved pre-training techniques, RoBERTa captures deep contextual relationships and performs well in a variety of natural language processing(NLP) tasks.
- BART (Lewis, 2019): Combines bidirectional encoding with autoregressive decoding, excelling in tasks that require both context understanding and coherent text generation, particularly in cross-domain scenarios.

Domain adaptation models are designed to address scenarios where the source and target domains have different data distributions. These models aim to adapt knowledge from the source domain to be effective in the target domain by aligning distributions, learning domain-invariant features, or using adversarial training to reduce the gap between domains.

- EANN (Wang et al., 2018): Uses an adaptive domain embedding network and adversarial training to learn shared representations between source and target domains. This approach addresses feature inconsistencies and distribution differences, enhancing the model's ability to generalize across different domains in multi-modal fake text detection.
- DANN (Ganin et al., 2016): Includes a feature extractor, classifier, and domain discriminator. Through adversarial training, it learns domain-invariant features, improving generalization across different domains.
- EDDFN (Silva, Luo, Karunasekera, & Leckie, 2021): Integrates domain embedding learning, domain-agnostic classification, and instance selection to enhance fake texts detection by leveraging both domain-specific and cross-domain knowledge while optimizing domain coverage in the labeled dataset.
- DRCN (Li & Caragea, 2020): Integrates an RNN classifier with a seq2seq autoencoder, sharing the encoder layer between both components. The encoder is trained to classify labeled source data while simultaneously reconstructing sequences from unlabeled target data, enabling domain adaptation.
- EAAF (Pei et al., 2024): Proposes an evidential learning framework for multi-source-free UDA, introducing Evidential Prediction Uncertainty for instance-level source preference estimation and evidential adjacency-consistent uncertainty for local semantic consistency. For fair comparison, we adapt it to the source-available setting aligned with our evaluation protocol.
- CADNN (Qu & Lyu, 2025): Introduces a unified framework that combines adversarial domain adaptation and cross-domain interpolation to address domain shift and class imbalance in emergency event classification. It learns domain-invariant features via a min–max game and aligns feature centroids to preserve data distribution across domains.

5.3.2. Comparative results analysis

We conduct UDA experiments using the MARDA model on the dataset and compare the results with those from the four model categories introduced in Section 5.3.1. The experimental results for the first three model categories in UDA across datasets for AD, ND, PHI, and SSI are presented in Tables 5, 6, 7, and 8, respectively. All experiments include domain-specific and overall performance metrics such as F1-Score, accuracy (ACC), and area under the ROC curve (AUC). Bold values indicate the best results. The following observations can be drawn:

1. Traditional machine learning models (e.g., BiLSTM, BiGRU, TextCNN, RoBERTa, and BART) significantly outperform traditional feature extraction methods (e.g., LDA, LIWC) across all metrics (ACC, AUC, and F1-Score) in domain adaptation tasks. This superior performance is due to the ability of transfer learning models to capture complex temporal and contextual information, whereas feature extraction methods rely on static text features that are less effective with dynamic and diverse data. For instance, BiLSTM's bidirectional structure enables it to comprehensively understand both forward and backward dependencies in the data, demonstrating enhanced adaptability in transfer learning tasks.

Table 5
Results of traditional and domain adaptation models for emergency event response detection: source domain as AD and other events as target domains.

	AD->AD	AD->ND	AD->PHI	AD->SSI		Overall	
	ACC	ACC	ACC	ACC	ACC	AUC	F1
Traditional feature extraction model							
LDA	0.8339	0.5845	0.6742	0.5409	0.6036	0.6199	0.5584
LIWC	0.8357	0.5861	0.6767	0.5404	0.6045	0.6208	0.5593
Traditional machine learning model							
BiLSTM	0.9125	0.6453	0.7218	0.6154	0.6709	0.7014	0.6424
BiGRU	0.9143	0.6474	0.7268	0.6144	0.6719	0.7023	0.6431
TextCNN	0.9143	0.6485	0.7268	0.6170	0.6734	0.7048	0.6453
Roberta	0.9143	0.6485	0.7293	0.6139	0.6724	0.7034	0.6440
BART	0.9179	0.6474	0.7293	0.6175	0.6738	0.7052	0.6464
Domain adaptation model							
EANN	0.9196	0.6526	0.7343	0.6175	0.6765	0.7099	0.6502
DANN	0.9214	0.6511	0.7318	0.6180	0.6761	0.7095	0.6494
EDDFN	0.9161	0.6516	0.7318	0.6175	0.6755	0.7082	0.6483
DRCN	0.9196	0.6500	0.7293	0.6186	0.6755	0.7089	0.6489
EAAF	0.9179	0.6485	0.7293	0.6154	0.6734	0.7016	0.6479
CADNN	0.9214	0.6516	0.7293	0.6165	0.6755	0.7081	0.6481
MARDA	**0.9679**	**0.6687**	**0.7569**	**0.6331**	**0.6967**	**0.7456**	**0.6757**

Table 6
Results of traditional and domain adaptation models for emergency event response detection: source domain as ND and other events as target domains.

	ND->AD	ND->ND	ND->PHI	ND->SSI		Overall	
	ACC	ACC	ACC	ACC	ACC	AUC	F1
Traditional feature extraction model							
LDA	0.6714	0.8268	0.5689	0.7582	0.7598	0.7879	0.7174
LIWC	0.6714	0.8253	0.5664	0.7577	0.7588	0.7870	0.7164
Traditional machine learning model							
BiLSTM	0.7446	0.9522	0.6341	0.8369	0.8554	0.8850	0.8468
BiGRU	0.7464	0.9548	0.6341	0.8390	0.8575	0.8872	0.8498
TextCNN	0.7464	0.9568	0.6341	0.8374	0.8577	0.8891	0.8505
Roberta	0.7464	0.9568	0.6341	0.8379	0.8579	0.8896	0.8512
BART	0.7464	0.9537	0.6341	0.8385	0.8569	0.8872	0.8487
Domain adaptation model							
EANN	0.7571	0.9761	0.6441	0.8562	0.8750	0.9088	0.8709
DANN	0.7571	0.9750	0.6441	0.8546	0.8740	0.9075	0.8693
EDDFN	0.7571	0.9776	0.6441	0.8562	0.8757	0.9096	0.8716
DRCN	0.7571	0.9797	0.6466	0.8567	0.8769	0.9103	0.8730
EAAF	0.7536	0.9698	0.6416	0.8525	0.8704	0.9028	0.8671
CADNN	0.7571	0.9787	0.6466	0.8562	0.8763	0.9088	0.8723
MARDA	**0.7804**	**0.9917**	**0.6591**	**0.8859**	**0.8971**	**0.9323**	**0.8985**

2. Domain adaptation models (e.g., EANN, DANN, DRCN, EDDFN, EAAF, and CADNN) exhibit higher accuracy, F1, and AUC scores compared to traditional machine learning models. These models incorporate domain-specific adaptation mechanisms such as adversarial training and adaptive weighting, which effectively address distributional differences between the source and target domains. For example, DANN employs a gradient reversal layer to perform adversarial learning, generating domain-invariant features and improving cross-domain adaptability.
3. Adversarial mechanisms (e.g., DANN, EANN, DRCN, CADNN, and MARDA) offer significant advantages in domain adaptation tasks. Experimental results indicate that models employing adversarial training outperform others by enhancing feature alignment between the source and target domains. For example, DANN reduces distributional differences through adversarial training, EANN optimizes domain embedding alignment, and MARDA applies adversarial perturbations to multi-view features, introducing regularization to prevent overfitting and leverage information redundancy. These results demonstrate that adversarial mechanisms improve model robustness and adaptability.
4. MARDA outperforms existing domain adaptation models across multiple target domains. On average, it achieves a 6.11% improvement in ACC, a 7.17% improvement in AUC, and a 7.39% improvement in F1-Score over all advanced baseline models. When compared solely with other domain adaptation models, MARDA delivers approximately a 3.42% boost in ACC, 4.33% in AUC, and 4.14% in F1 across the four source domains. Furthermore, relative to traditional models, MARDA exhibits even more

Table 7
Results of traditional and domain adaptation models for emergency event response detection: source domain as PHI and other events as target domains.

	PHI->AD	PHI->ND	PHI->PHI	PHI->SSI	Overall		
	ACC	ACC	ACC	ACC	ACC	AUC	F1
				Traditional feature extraction model			
LDA	0.6196	0.5965	0.8020	0.5164	0.5843	0.6205	0.5672
LIWC	0.6214	0.5970	0.8020	0.5164	0.5847	0.6213	0.5684
				Traditional machine learning model			
BiLSTM	0.7018	0.6667	0.8772	0.5847	0.6555	0.6823	0.6281
BiGRU	0.7018	0.6661	0.8797	0.5842	0.6553	0.6821	0.6275
TextCNN	0.7018	0.6667	0.8797	0.5847	0.6557	0.6837	0.6295
Roberta	0.7018	0.6667	0.8797	0.5847	0.6557	0.6836	0.6285
BART	0.7018	0.6677	0.8797	0.5852	0.6563	0.6845	0.6296
				Domain adaptation model			
EANN	0.7107	0.6739	0.9073	0.5961	0.6665	0.6974	0.6394
DANN	0.7107	0.6719	0.9073	0.5956	0.6655	0.6948	0.6368
EDDFN	0.7214	0.6734	0.9098	0.5951	0.6674	0.6976	0.6407
DRCN	0.7107	0.6724	0.9073	0.5961	0.6659	0.6964	0.6386
EAAF	0.7071	0.6693	0.9023	0.5899	0.6613	0.6899	0.6320
CADNN	0.7125	0.6729	0.9073	0.5951	0.6659	0.6959	0.6392
MARDA	**0.7411**	**0.7124**	**0.9424**	**0.6144**	**0.6957**	**0.7314**	**0.6703**

Table 8
Results of traditional and domain adaptation models for emergency event response detection: source domain as SSI and other events as target domains.

	SSI->AD	SSI-> ND	SSI-> PHI	SSI-> SSI	Overall		
	ACC	ACC	ACC	ACC	ACC	AUC	F1
				Traditional feature extraction model			
LDA	0.6929	0.7088	0.6090	0.8525	0.7561	0.7740	0.7296
LIWC	0.6929	0.7093	0.6090	0.8541	0.7569	0.7741	0.7309
				Traditional machine learning model			
BiLSTM	0.7554	0.7930	0.6767	0.9427	0.8388	0.8571	0.8268
BiGRU	0.7554	0.7936	0.6767	0.9453	0.8400	0.8577	0.8284
TextCNN	0.7554	0.7930	0.6767	0.9448	0.8396	0.8578	0.8278
Roberta	0.7554	0.7920	0.6767	0.9437	0.8388	0.8559	0.8268
BART	0.7536	0.7925	0.6767	0.9432	0.8386	0.8552	0.8262
				Domain adaptation model			
EANN	0.7679	0.8112	0.6842	0.9588	0.8546	0.8761	0.8467
DANN	0.7679	0.8102	0.6842	0.9594	0.8544	0.8747	0.8469
EDDFN	0.7679	0.8081	0.6817	0.9567	0.8523	0.8724	0.8448
DRCN	0.7679	0.8107	0.6817	0.9583	0.8540	0.8760	0.8472
EAAF	0.7625	0.8066	0.6792	0.9531	0.8494	0.8679	0.8395
CADNN	0.7679	0.8092	0.6867	0.9573	0.8534	0.8751	0.8463
MARDA	**0.7982**	**0.8388**	**0.7193**	**0.9838**	**0.8821**	**0.9095**	**0.8802**

substantial gains, with average improvements of about 8.42% in ACC, 9.61% in AUC, and 10.17% in F1. Overall, MARDA's improvements over traditional models are nearly 1.8 times greater than those achieved by domain adaptation models alone. This 1.8-fold increase underscores the efficacy of MARDA's innovative architecture. This success mainly stems from three key innovations: (1) a cross-view processor that integrates semantic, emotional, and adversarially enhanced features to generate domain-invariant representations; (2) an adversarial cross-view optimizer that enhances feature robustness through consistency-regularized adversarial training; and (3) an adaptive weighted domain enhancer that dynamically balances multi-view feature contributions, optimizing cross-domain feature fusion and classification accuracy.

5.4. Comparison of large language model

Large language models (LLMs) are cutting-edge models pre-trained on massive amounts of text data. These models excel at understanding language patterns, context, and relationships between words at scale, making them highly effective for a variety of NLP tasks. In this experiment, GPT-4 and DeepSeek are used in a zero-shot setting, while T5-base and LLaMA-7B are fine-tuned for specific tasks.

Table 9
Results of large language models for emergency event response detection: source domain as SSI and other events as target domains.

	SSI->AD	SSI->ND	SSI->PHI	SSI->SSI	Overall		
	ACC	ACC	ACC	ACC	ACC	AUC	F1
			Large language models (Zero-Shot)				
GPT-4	**0.9018**	0.5497	**0.9098**	0.5502	0.6209	0.5626	0.4668
DeepSeek	0.8875	0.5601	0.8997	0.5440	0.6201	0.5705	0.4704
			Large language models (Fine-tuned)				
T5-base	0.7839	0.8133	0.6967	0.9838	0.8683	0.8902	0.8634
Llama-7B	0.7893	0.8206	0.7043	**0.9870**	0.8738	0.8977	0.8694
			Domain adaptation models				
MARDA	0.7982	**0.8388**	0.7193	0.9838	**0.8821**	**0.9095**	**0.8802**

- GPT-4 (Achiam et al., 2023): A state-of-the-art language model developed by OpenAI, GPT-4 excels in generating human-like text and understanding complex instructions. It demonstrates strong performance across a wide range of NLP tasks, including text classification, summarization, and translation.
- DeepSeek (Liu et al., 2024): A large-scale language model focused on understanding and generating both structured and unstructured text. It specializes in knowledge extraction and contextual understanding, making it highly effective for applications like document analysis and question answering.
- T5-base (Raffel et al., 2020): A versatile pre-trained transformer model that formulates all NLP tasks as text-to-text problems. T5-base is widely adopted for tasks such as text classification, summarization, translation, and text generation.
- LLaMA-7B (Dubey et al., 2024; Touvron et al., 2023): A powerful language model in the LLaMA family, LLaMA-7B is designed for a wide variety of NLP tasks, such as text generation, classification, and summarization, offering strong performance and efficiency across different applications.

We present a comparative analysis focusing on the SSI domain, as shown in Table 9. Large language models, such as GPT-4, DeepSeek, T5-base, and Llama-7B, exhibit varying levels of performance in cross-domain tasks. Zero-shot models like GPT-4 and DeepSeek perform well in certain domain transfers (e.g., SSI->AD) but struggle in others (e.g., SSI->ND and SSI->PHI). This is primarily due to their tendency to misclassify all categories into a single class, reflecting a lack of effective domain adaptation and resulting in suboptimal cross-domain performance. Fine-tuned models, such as T5-base and Llama-7B, achieve strong results in the source domain (SSI-> SSI), but their ability to transfer knowledge across domains is limited. This limitation likely arises from an over-reliance on source-domain features during fine-tuning, which hinders their generalization capability. In contrast, MARDA effectively employs domain adaptation mechanisms to capture feature distributions across different domains and optimize feature representation learning, leading to superior cross-domain performance. Specifically, MARDA outperforms fine-tuned LLMs, achieving an average improvement of 1.27% in accuracy, 1.74% in AUC, and 1.59% in F1, demonstrating its effectiveness in domain adaptation.

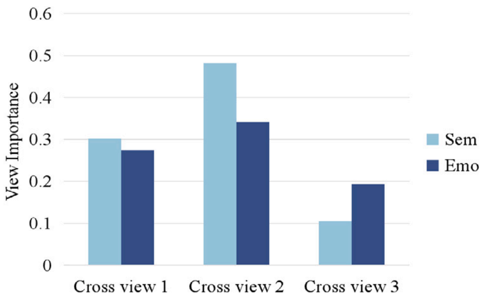
5.5. Importance variation across views

In this section, we conduct experiments on four emergency event datasets to verify the effectiveness of MARDA in modeling domain variations. Due to significant domain differences, the discriminative features of each domain vary across cross-view representations. To address this challenge, MARDA extracts key cross-view features to optimize transfer learning performance. The number of heads in the adaptive weighted domain enhancer (Z) is set to 3, and the number of channels in the cross-view processor (n_{sem} and n_{emo}) is set to 1.

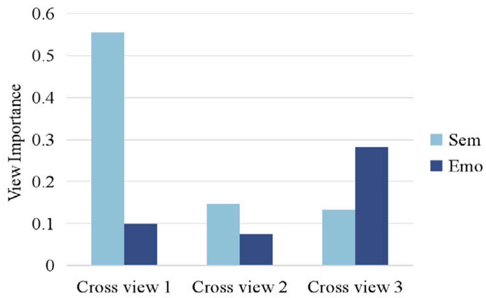
We first visualize the adaptive weights w_i^{sem} and w_j^{emo} for the three cross-views (as shown in Fig. 5). The results indicate that the cross-views generated by MARDA show noticeable differences in the combination of semantic and emotional views, and this diversity helps capture inter-domain differences more effectively. Additionally, we visualize the importance of each cross-view representation in the four domains (as shown in Fig. 6). The results reveal that the discriminative power of cross-views differs across domains, further validating the effectiveness of MARDA in modeling domain differences. To enhance domain adaptation, an adversarial cross-view optimizer is introduced. By adding controlled noise between domains, the model can better capture these differences, improving feature alignment and transfer learning performance.

The experimental results demonstrate that our model successfully extracts diverse cross-view features and dynamically adjusts the weights based on domain characteristics. This cross-view feature extraction method enhances the model's adaptability and robustness, maintaining strong classification performance in cross-domain tasks. By leveraging different types of information, the model improves overall classification outcomes.

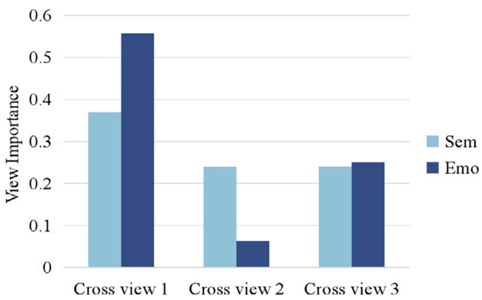
In the SSI domain, the weights of the semantic and emotional views are relatively balanced, underscoring the critical role of emotional features in classification tasks. In the AD domain, the semantic view dominates, reflecting its significance in accident-related events, though emotional features remain important. In the PHI domain, emotional views are prominent in the first view, while weights of semantic and emotional views are more balanced in other views, demonstrating the model's adaptability to shifts in



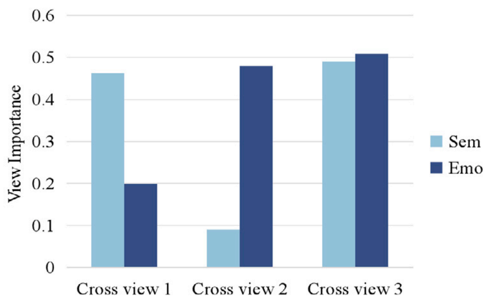
(a) View importance of AD



(b) View importance of ND



(c) View importance of PHI



(d) View importance of SSI

Fig. 5. Figures (a)–(d) denote the importance of different views in a cross-view interaction.

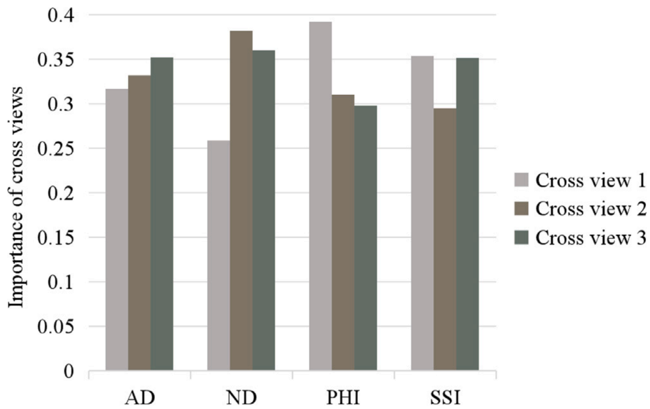


Fig. 6. Various importances of four cross-view interactions for different domains.

feature importance. In the ND domain, the semantic view carries more weight in certain contexts, but emotional features also become more influential under specific conditions, showcasing the model's ability to capture and utilize changes in feature importance effectively.

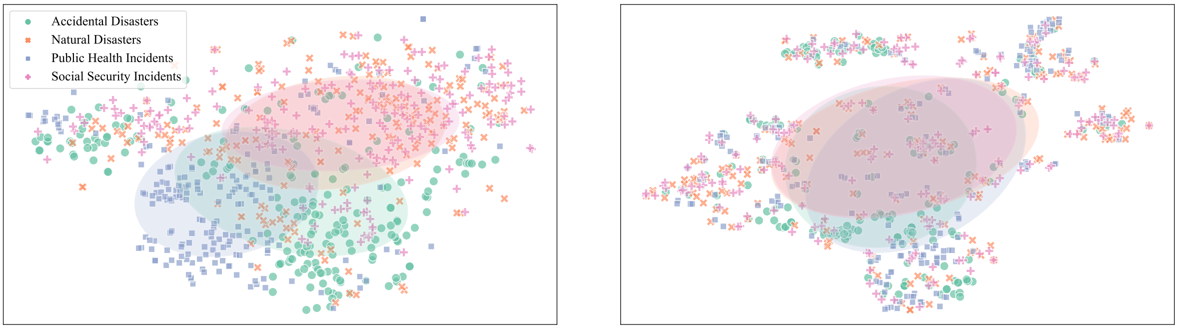
5.6. Ablation study results

In the ablation study of the MARDA model, we carefully examine the impact of each component on the model's overall performance, revealing their distinct roles and interdependence in domain adaptation learning. The detailed results are presented in Table 10.

The removal of the semantic processor results in the largest performance drop of 16.14% in F1-Score, highlighting its pivotal role in cross-domain emergency event classification. As shown in the t-SNE visualization of the processors' outputs in Fig. 7, semantic

Table 10
Results of ablation study on SSI dataset.

Model component	ACC	AUC	F1
MARDA	**0.8821**	**0.9095**	**0.8802**
w/o SemPro	0.7688	0.7996	0.7579
w/o EmoPro	0.8225	0.8484	0.8157
w/o Interactors	0.8517	0.8761	0.8486
w/o Adversarial Optimizer	0.8619	0.8884	0.8547
w/o Domain Enhancer	0.8307	0.8544	0.8226



(a) Semantic processor output (b) Emotion processor output

Fig. 7. T-SNE visualization of processor outputs.

features exhibit increased overlap across event categories compared to the initial features in Fig. 1(a), demonstrating their strong ability to capture domain-invariant concepts and facilitate robust generalization across diverse lexical expressions. In contrast, removing the emotional processor leads to a smaller but still notable 7.91% decrease in performance, indicating its complementary contribution. Emotional features display high category overlap but a more dispersed sample distribution, suggesting an auxiliary role in enriching the representation space with nuanced affective information that complements the semantic features.

The removal of the interactors caused a 3.72% decrease in the F1-Score, demonstrating the value of integrating cross-view information to enhance the model's discriminative capacity. The interactors allow the model to better understand various emergency events by analyzing features from different domains from multiple perspectives. Additionally, removing the adversarial cross-view optimizer led to a 2.98% decrease in the F1-Score, reaffirming the critical role of the adversarial network in reducing feature distribution differences between source and target domains. Finally, eliminating the adaptive weighted domain enhancer caused a 7.00% decrease in the F1-Score, underscoring the importance of the adaptive weighted domain enhancer in aggregating and optimizing cross-view feature representations. The module facilitates smooth information transfer across different domains by integrating cross-view information, thus improving the model's adaptability and generalization.

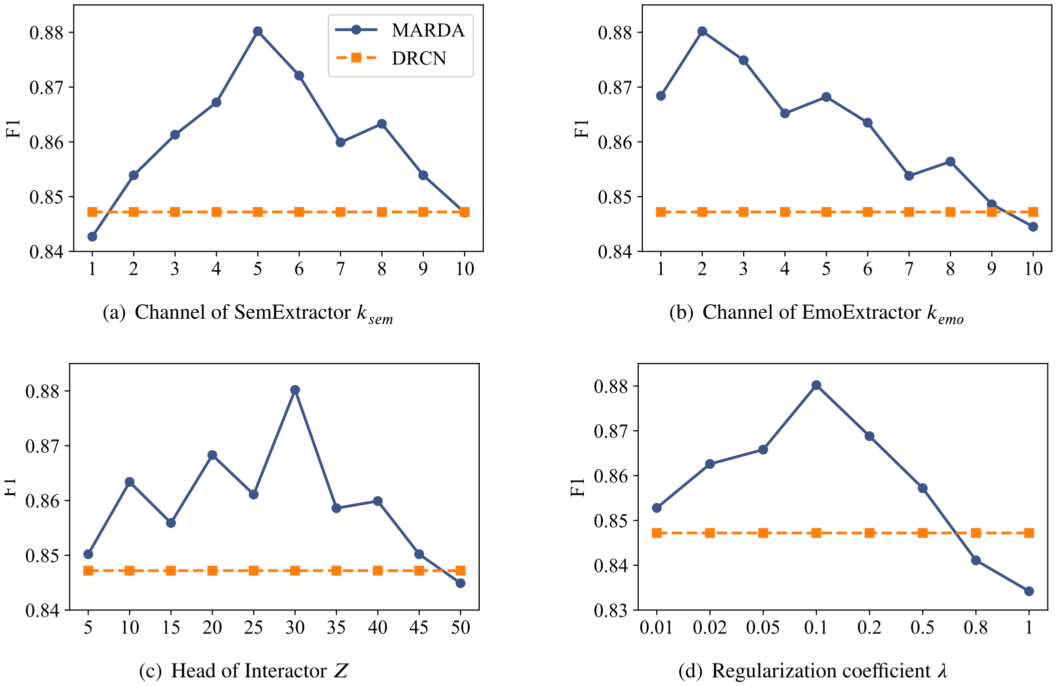
5.7. Parameter sensitivity analysis

In this section, we investigate the sensitivity of various hyperparameters in the MARDA model, focusing on the semantic, emotional, and view channels, as well as the adversarial network. The experimental results, presented in Fig. 8, reveal some variability in performance as parameters change. However, across all tested configurations, MARDA consistently outperforms the state-of-the-art models, demonstrating that it is not highly parameter-sensitive in the conventional sense. The model maintains competitive performance over a broad and practical range of hyperparameter values.

Specifically, the results show variability in the performance of the semantic channel with different parameter settings. The model achieves its peak F1-score when the semantic parameter, n_{sem}, is set to 5. Further adjustments beyond this point lead to overfitting and a subsequent decline in performance. In contrast, the emotional channel exhibits more stability, with only minor fluctuations in performance. The F1-score reaches its maximum when the emotional parameter, n_{emo}, is set to 2, suggesting that moderate tuning enhances the contribution of emotional features to the classification task.

The view channel tuning results show some volatility, with the F1-score peaking at a parameter setting of 30, followed by a slight decline. Although its impact is less pronounced compared to the semantic and emotional channels, it still contributes to overall performance improvement. Adjusting the adversarial network parameters is particularly critical: the F1-score increases initially, reaching its highest value when the regularization coefficient λ is set to 0.1, before declining with further adjustments. This indicates that careful tuning of the adversarial network can significantly enhance the model's generalization ability.

These findings confirm MARDA's robustness and sustained superiority over competing models across diverse hyperparameter settings. The identified optimal ranges form a generalizable region in the hyperparameter space, enabling effective application to different datasets and domains.



(a) Channel of SemExtractor k_{sem}

(b) Channel of EmoExtractor k_{emo}

(c) Head of Interactor Z

(d) Regularization coefficient λ

Fig. 8. Performance (F1-Score) of MARDA with various hyperparameters.

6. Discussion

Theoretical Implications: Our work introduces a novel integration of adversarial domain adaptation with multi-view feature learning, fundamentally advancing our understanding of domain discrepancies in emergency event classification. Specifically, MARDA's architecture comprises a cross-view processor, an adaptive weighted domain enhancer, and an adversarial cross-view optimizer, offers insights into the interplay between semantic and emotional features and their collective impact on effective domain adaptation. This integrated approach not only mitigates the adverse effects of domain shifts but also enriches the theoretical framework by demonstrating that aligning diverse feature views is crucial for achieving robust cross-domain performance. Unlike prior studies that have primarily focused on single-domain or limited feature representations, our method explicitly models multi-view relationships, providing a more nuanced understanding of the dynamics among different feature modalities.

Practical Implications: On the practical front, MARDA addresses critical challenges encountered in real-world emergency event detection on social media. By effectively aligning feature distributions across diverse emergency domains (e.g., ND, AD, PHI, and SSI), MARDA significantly enhances the model's adaptability and generalization capabilities. This is reflected in superior cross-domain performance, with improvements of approximately 7.39% in average F1-Score and a 1.8-fold performance gain over traditional domain adaptation methods. These advancements render MARDA a scalable and robust solution for emergency event classification in environments characterized by high data heterogeneity. Its ability to dynamically balance feature contributions and minimize distributional discrepancies ensures broad applicability to diverse and complex datasets in real-world scenarios.

Distinctiveness from Existing Work: Unlike existing approaches that often rely solely on statistical alignment, adversarial learning, or generative techniques in isolation, our research is the first to combine adversarial domain adaptation with multi-view feature learning within a unified framework tailored for emergency event classification. Our approach specifically addresses the pronounced differences in linguistic and emotional characteristics across multiple public emergency domains. It demonstrates that effective cross-domain knowledge transfer requires not only robust feature alignment but also the dynamic balancing of semantic and emotional cues—challenges that previous methods have not fully tackled. Overall, MARDA's innovative design and empirical improvements indicate both its theoretical contributions to domain adaptation research and its practical effectiveness in navigating the complexities of real-world emergency event detection.

Future Work: Although MARDA achieves notable advancements in cross-domain emergency event classification, several promising research directions warrant further investigation. One potential extension involves integrating external knowledge sources, such as structured knowledge graphs and real-time event streams, to enhance the richness and contextual relevance of semantic and emotional representations, particularly in scenarios with limited labeled data. Another avenue is to adapt MARDA to few-shot and continual learning frameworks, thereby improving its ability to accommodate emerging emergency events and dynamic domain shifts with minimal supervision. Additionally, expanding MARDA to incorporate multiple data modalities, including textual, visual, and geospatial information, is expected to strengthen its robustness and applicability in complex, real-world emergency response situations.

7. Conclusion

In this work, we propose a novel framework called MARDA, which combines multi-view feature learning with adversarial domain adaptation for emergency event classification. MARDA focuses on cross-domain classification and aims to tackle domain shifts caused by discrepancies in emergency events. First, given the variation in linguistic features and emotional expressions across domains, a cross-view processor is designed to extract and integrate semantic and emotional features. This generates comprehensive multi-view representations, enabling diverse view combinations and effectively modeling domain discrepancies. Second, to further enhance classification accuracy across domains, an adaptive weighted domain enhancer is employed to dynamically balance contributions from multiple views, effectively aggregating discriminative information across multi-view representations. Third, to mitigate distribution discrepancies across domains, an adversarial cross-view optimizer is applied, employing a minimax game and feature consistency regularization to reduce domain-specific interference and enhance generalization. Extensive experiments demonstrate that MARDA significantly outperforms state-of-the-art methods, achieving superior F1-Score and excelling in cross-domain adaptability. These results validate MARDA as a robust and generalized solution for cross-domain emergency event classification, with each component playing a critical role in addressing domain shifts.

CRediT authorship contribution statement

Yuhan Xie: Writing – original draft, Visualization, Validation, Methodology, Formal analysis. **Chen Lyu:** Writing – review & editing, Supervision, Conceptualization. **Zheng Qu:** Data curation, Conceptualization. **Chunmei Liu:** Supervision, Funding acquisition.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work we used ChatGPT in order to correct grammatical errors and improve readability. After using this tool, we reviewed and edited the content as needed and take full responsibility for the content of the publication.

Acknowledgment

This work was supported by the National Key R&D Program of China (2023YFA1009500), and the Ministry of Education of China (MOE) Project of Humanities and Social Sciences (Grant 24YJCZH197).

Data availability

Data will be made available on request.

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