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An integrated deep CNN–LSTM framework for disaster management through reliable information retrieval and educational awareness

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ABSTRACT

Background: Social media has become one of the primary sources of disaster-related information; however, the rapid dissemination of heterogeneous, duplicated, and misleading content presents significant challenges for retrieving reliable information that can support disaster management and educational awareness. Conventional machine learning approaches often struggle to simultaneously capture semantic representations and contextual dependencies within large-scale disaster communications.

Aims: This study aims to develop and evaluate an integrated Deep CNN–LSTM-based disaster management framework for retrieving reliable disaster-related information from heterogeneous online sources while supporting educational awareness through safe information dissemination.

Methods: A quantitative experimental design was employed using disaster-related textual datasets collected from multiple online platforms, including earthquake, flood, wildfire, and COVID-19 events. The proposed framework integrated Deep Convolutional Neural Networks (Deep CNN) for semantic feature extraction with Long Short-Term Memory (LSTM) networks for sequential contextual learning. Model performance was compared with six benchmark machine learning and deep learning approaches, namely Support Vector Machine (SVM), Neural Network (NN), Feed-forward Neural Network (FFNN), Recurrent Neural Network (RNN), LSTM, and Hybrid CNN–LSTM. The framework was evaluated using retrieval performance together with Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2).

Result: The proposed framework consistently retrieved a greater amount of relevant disaster-related information across multiple disaster scenarios than the benchmark models. Quantitative evaluation further demonstrated robust predictive capability, achieving an RMSE of 15,286.2154, an MAE of 13,789.75, and the highest coefficient of determination ($R^2 = 0.9793$), indicating strong model fitting and reliable predictive performance.

Conclusion: The integrated Deep CNN–LSTM framework effectively combines semantic feature extraction and contextual sequence learning to improve disaster information retrieval from heterogeneous online sources. The proposed framework contributes to intelligent disaster management by providing reliable disaster-related information that supports educational awareness and evidence-based decision-making during disaster preparedness and emergency response.

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INTRODUCTION

Natural disasters continue to pose significant threats to human life, public health, economic stability, and environmental sustainability. In addition to causing physical destruction, disaster events frequently create complex information environments in which emergency responders, decision-makers, and affected communities must rapidly distinguish reliable information from misinformation, incomplete reports, and communication overload. The effectiveness of disaster management therefore depends not only on emergency response capabilities but also on the availability of trustworthy information and the preparedness of communities to interpret and act upon such information appropriately. Within this context, education has become an essential component of disaster risk reduction because it enhances public awareness, strengthens preparedness, and equips individuals with the knowledge and skills required to respond effectively before, during, and after disasters. Torani et al. (2019) emphasized that educational outreach represents an operationally effective and economically sustainable strategy for improving disaster preparedness and reducing disaster risks through continuous public education.

The rapid expansion of social media has fundamentally transformed the way disaster-related information is generated, shared, and consumed. During emergency situations, platforms such as Twitter, Facebook, and other online communication channels enable real-time dissemination of situational updates, requests for assistance, and public warnings, thereby providing valuable information for emergency management. At the same time, the enormous volume, heterogeneity, and varying credibility of user-generated content present substantial challenges for identifying relevant information while minimizing misinformation and information overload. To address these challenges, numerous intelligent information retrieval systems have been developed to collect, filter, and analyze disaster-related content from online environments. Bouzidi et al. (2019) proposed a real-time alert model that integrates information retrieval from multiple sources to improve disaster management, while Bouzidi et al. (2020a) extended this direction by developing an automated learning environment through social media to strengthen disaster education. Subsequently, Bouzidi et al. (2021) provided a comprehensive survey highlighting the growing integration of deep learning techniques and social media analytics for disaster management. Collectively, these studies demonstrate substantial progress in utilizing artificial intelligence to support disaster-related information management, although most existing approaches remain focused on limited information sources or specific disaster management functions.

Although recent advances in artificial intelligence and social media analytics have substantially improved disaster-related information retrieval, several important limitations remain. Existing studies have primarily focused on retrieving relevant disaster content, classifying emergency messages, or generating real-time alerts from online platforms rather than supporting disaster management through an integrated educational perspective. Information retrieval techniques based on multiple online sources have demonstrated their potential for improving emergency monitoring and early warning (Bouzidi et al., 2019), while automated learning environments have been proposed to facilitate disaster education through social media (Bouzidi et al., 2020a; Bouzidi et al., 2020b). Similarly, comprehensive reviews have highlighted the growing contribution of deep learning to disaster management, particularly in information extraction, content classification, and emergency communication (Bouzidi et al., 2021). Other studies have investigated WebGIS technologies for emergency response (Abdalla & Ali, 2019), emergency tweet classification (Lamsal & Kumar, 2020), social media behavior during unexpected disasters (Olteanu et al., 2015), and information retrieval using semantic representations (Vulić & Moens, 2015). Collectively, these studies demonstrate significant progress in intelligent disaster information processing. Nevertheless, most existing approaches remain oriented toward technical retrieval performance, with comparatively limited attention devoted to integrating trustworthy information, educational awareness, and decision support within a unified disaster management framework.

The identification of relevant disaster information can be formulated as a sequence learning problem because meaningful knowledge emerges from continuously evolving streams of heterogeneous textual information originating from multiple online sources. Such information is characterized by temporal dependency, semantic variability, and varying levels of credibility, making conventional machine learning approaches less effective for capturing contextual relationships. Deep learning architectures have therefore become increasingly attractive because they automatically learn hierarchical representations from complex textual data. Convolutional Neural Networks (CNNs) are particularly effective for extracting discriminative local textual features, whereas Long Short-Term Memory (LSTM) networks preserve long-term sequential dependencies that are essential for understanding evolving disaster-related communications (Bouzidi et al., 2021; Bianchi et al., 2017). Previous studies have successfully applied recurrent neural networks and LSTM models to forecasting, disaster monitoring, financial prediction, and automated learning environments (Bouzidi et al., 2021b; Bouzidi et al., 2022; Bouzidi et al., 2021c), demonstrating the effectiveness of hybrid deep learning architectures for processing sequential information. Despite these advances, most existing models emphasize prediction accuracy and information retrieval efficiency without explicitly transforming validated disaster information into educational awareness capable of supporting preparedness, informed decision-making, and long-term community resilience. Consequently, opportunities remain to develop an integrated framework that not only retrieves reliable information from multiple sources but also enhances disaster management through educational awareness and safe information dissemination.

Despite the considerable progress achieved in disaster-related information retrieval and deep learning applications, the existing body of literature reveals several unresolved research gaps. First, most previous studies have investigated disaster management, information retrieval, educational outreach, or deep learning as independent research directions rather than integrating them into a comprehensive disaster management framework (Torani et al., 2019; Bouzidi et al., 2019; Bouzidi et al., 2020a; Bouzidi et al., 2021). Second, the majority of existing disaster information systems concentrate on detecting disaster-related content or generating alerts, while comparatively limited attention has been devoted to validating the reliability of retrieved information before it is disseminated to the public (Abdalla & Ali, 2019; Bouzidi et al., 2021). This limitation is particularly important because inaccurate or misleading information disseminated during emergencies may amplify public confusion, delay emergency response, and reduce community trust in disaster communication systems. Third, although hybrid deep learning architectures have demonstrated promising predictive capabilities across various sequential learning tasks, their application has rarely been designed to transform validated disaster information into educational knowledge that actively supports public awareness, preparedness, and sustainable disaster risk reduction (Bouzidi et al., 2020b; Bouzidi et al., 2021; Lamsal & Kumar, 2020). Consequently, there remains a need for an integrated framework capable of simultaneously retrieving reliable disaster information, filtering misleading content, and supporting educational awareness as complementary components of intelligent disaster management.

To address these challenges, this study proposes an integrated disaster management framework that combines educational outreach, safe information retrieval, and hybrid deep learning within a unified intelligent decision-support environment. The proposed framework employs a Deep Convolutional Neural Network–Long Short-Term Memory (Deep CNN–LSTM) architecture to retrieve and identify relevant disaster-related information from multiple social media sources while reducing the influence of duplicate content, misinformation, and irrelevant messages (Bouzidi et al., 2019; Bouzidi et al., 2020a; Bouzidi et al., 2021). Beyond improving information retrieval performance, the framework is designed to strengthen educational awareness by transforming validated disaster information into actionable knowledge that supports emergency preparedness, informed decision-making, and public participation throughout different phases of disaster management. Accordingly, the objective of this study is to develop and evaluate an integrated Deep CNN–LSTM-based disaster management framework for retrieving reliable disaster-related information from multiple online sources while supporting disaster preparedness and educational awareness through the dissemination of validated information.

METHOD

Research Design

This study employed a quantitative computational research design to develop and evaluate an intelligent disaster management framework that integrates educational awareness, reliable information retrieval, and hybrid deep learning techniques. The study was designed as a framework-development research because its primary objective was to construct an integrated computational model capable of retrieving trustworthy disaster-related information from heterogeneous online sources while supporting educational awareness and informed disaster management. Unlike conventional disaster information systems that primarily focus on information retrieval or alert generation, the proposed framework incorporates data acquisition, preprocessing, feature learning, sequential modeling, and performance evaluation within a unified decision-support environment. This integrated design enables reliable disaster information to be systematically identified, filtered, and transformed into actionable knowledge for emergency preparedness and disaster risk reduction.

To ensure a systematic implementation, the research framework was organized into five sequential stages, namely data acquisition, data preprocessing, deep feature extraction, sequential learning, and performance evaluation. The workflow begins with collecting disaster-related textual information from multiple online sources, followed by preprocessing procedures to improve data quality through cleaning, normalization, duplicate removal, and misinformation filtering. The processed textual data are subsequently transformed into semantic feature representations and analyzed using the proposed Deep CNN–LSTM architecture. Finally, the resulting disaster-related information is evaluated using quantitative performance metrics before being utilized to support educational awareness and disaster management decision-making. The overall research workflow adopted in this study is illustrated in Figure 1.

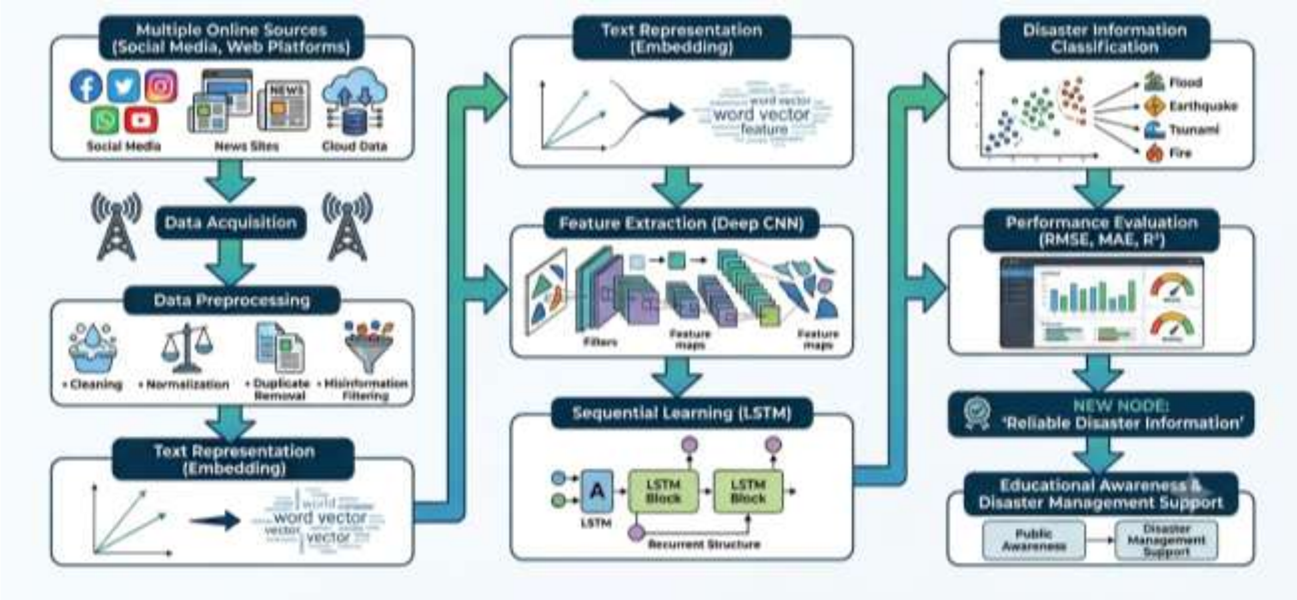

Figure 1. Research Framework of the Proposed Deep CNN–LSTM-Based Disaster Management System

Figure 1 presents the overall workflow of the proposed disaster management framework. The framework begins with the acquisition of disaster-related information from multiple online sources and continues with preprocessing to improve the quality and reliability of textual data. The processed information is subsequently analyzed through the proposed Deep CNN–LSTM architecture to extract semantic features and model contextual dependencies for accurate disaster information classification. The classified information is then evaluated using predefined quantitative metrics before being utilized to support educational awareness and informed disaster management.

Data Collection and Preprocessing

Disaster-related textual data were collected from multiple online information sources, including social media platforms, web-based news portals, and cloud-based repositories that continuously disseminate disaster-related information. A multi-source acquisition strategy was adopted to improve information diversity and reduce dependence on a single communication platform, thereby providing broader coverage of disaster events and public communications. Data collection was performed using predefined disaster-related keywords, hashtags, and event-specific queries to retrieve heterogeneous textual information associated with natural disasters, emergency responses, and situational updates. The collected textual corpus constituted the primary dataset used for subsequent model development and experimental evaluation.

Prior to model development, the collected data underwent a comprehensive preprocessing procedure to improve data quality and semantic consistency. Initially, incomplete, duplicated, and irrelevant records were removed to reduce redundancy and eliminate noise within the dataset. The remaining textual data were subsequently normalized through standard text cleaning and tokenization procedures to produce consistent textual representations suitable for machine learning. Considering that disaster-related information obtained from online environments may contain misinformation or non-disaster-related content, an additional filtering stage was applied to retain only validated disaster-related information. The resulting preprocessed corpus was then transformed into embedded numerical representations, which served as the input for the proposed Deep CNN–LSTM architecture described in the following section (Bouzidi et al., 2019; Bouzidi et al., 2020a; Bouzidi et al., 2021).

Proposed Deep CNN–LSTM Architecture

The proposed disaster information processing framework employs a hybrid Deep CNN–LSTM architecture to identify relevant disaster-related information from heterogeneous textual data collected from multiple online sources. The architecture integrates the complementary capabilities of Deep CNN and LSTM. The Deep CNN component is intended to extract informative local patterns from textual representations, whereas the LSTM component captures long-term contextual dependencies within disaster-related message sequences. Through this integration, the framework processes both the semantic characteristics of individual messages and the contextual relationships that evolve across sequential communications.

Following preprocessing, each disaster-related message is represented as an ordered sequence of words. Let $e$denote an input message consisting of $n$words drawn from a finite vocabulary V:

$$e = (w_1, \dots, w_i, \dots, w_n), w_i \in V \qquad (1)$$

Equation (1) defines the textual input supplied to the proposed architecture. Each message is treated as a sequence of lexical elements that can subsequently be transformed into numerical representations for feature extraction and sequential learning. This formulation preserves the ordered structure of the message and provides the basis for processing keywords, hashtags, and other disaster-related textual indicators.

During supervised model training, the prediction error is calculated using a logarithmic loss function. For a positive observation ($y = 1$), the loss is expressed as:

$$-\ln p(x) \qquad (2)$$

where $p(x)$denotes the probability assigned by the model to the positive class. Conversely, for a negative observation ($y = 0$), the loss is:

$$-\ln(1 - p(x)) \qquad (3)$$

The two cases are combined into the binary cross-entropy function:

$$\mathcal{L}(y, p(x)) = -y \ln p(x) - (1 - y) \ln(1 - p(x)) \qquad (4)$$

Equation (4) measures the discrepancy between the predicted probability and the actual class label. Minimizing this loss during training enables the model to distinguish relevant disaster-related messages from irrelevant or non-informative content.

The embedded textual representations are subsequently processed by the Long Short-Term Memory (LSTM) network to model contextual dependencies among disaster-related messages. Unlike conventional recurrent neural networks, LSTM incorporates an internal memory mechanism that selectively retains relevant contextual information while discarding less informative patterns through a series of gating operations. This capability enables the proposed model to capture long-term semantic dependencies that frequently occur in disaster-related communications.

The first stage of the LSTM architecture is the input gate, which regulates the amount of newly extracted semantic information incorporated into the memory cell. Simultaneously, the memory cell is updated by integrating the retained historical information with the newly generated candidate state. These operations are formulated as

$$i_t = \sigma(\omega_{ix}x_t + \omega_{ih}h_{t-1} + b_i) \qquad (5)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(\omega_{cx}x_t + \omega_{ch}h_{t-1} + b_c) \qquad (6)$$

where $i_t$denotes the input gate activation, $c_t$represents the updated memory cell, $x_t$is the current input vector, $h_{t-1}$is the previous hidden state, and $b_i$and $b_c$denote the corresponding bias vectors. Equations (5) and (6) regulate how newly extracted semantic features are incorporated into the memory while preserving previously learned contextual information.

The forget gate subsequently determines the proportion of historical information retained for the next learning step and is expressed as

$$f_t = \sigma(\omega_{fx}x_t + \omega_{fh}h_{t-1} + b_f) \qquad (7)$$

where $f_t$controls the retention or removal of contextual information stored in the memory cell. This mechanism enables the network to eliminate irrelevant contextual patterns while maintaining disaster-related semantic information required for subsequent prediction.

The contextual representation generated by the updated memory cell is propagated through the output gate, which determines the hidden representation used for disaster information classification.

$$j_t = \sigma(\omega_{jx}x_t + \omega_{jh}h_{t-1} + b_j) \qquad (8)$$
$$h_t = j_t \odot \tanh(c_t) \qquad (9)$$

where $j_t$denotes the output gate activation and $h_t$represents the hidden state generated from the updated memory cell. Together, Equations (8) and (9) produce the contextual representation that summarizes both semantic and sequential characteristics of disaster-related textual information before classification.

The hidden representation is subsequently transformed through the network state and output layers according to

$$h_t = f(h_{t-1}, x_t) \qquad (10)$$
$$h_t = \tanh(\sigma_{hh}h_{t-1} + \sigma_{xh}x_t) \qquad (11)$$
$$y_t = \sigma_{hy}h_t \qquad (12)$$
$$h_t = \alpha(\sigma_{hx}x_t + \sigma_{hh}h_{t-1} + b_h) \qquad (13)$$
$$y_t = \beta(\sigma_{yh}h_t + b_y) \qquad (14)$$

where $h_t$denotes the hidden state, $y_t$is the output prediction, σrepresents the network weights, $b$denotes the bias vectors, $\alpha$is the hidden-layer activation function, and $\beta$is the output-layer activation function. These operations complete the forward propagation process and generate the final disaster information classification used in the proposed disaster management framework.

Model Training and Performance Evaluation

The proposed Deep CNN–LSTM architecture was trained using a supervised learning strategy to classify disaster-related textual information into relevant disaster categories. During the training process, the embedded textual representations were propagated through the convolutional and sequential learning layers, where network parameters were iteratively optimized by minimizing the prediction error between the estimated outputs and the corresponding ground-truth labels. The optimization process employed the binary cross-entropy loss function described in Equations (2)–(4), allowing the model to continuously adjust its internal parameters through backpropagation until convergence. By integrating convolution-based semantic feature extraction with sequential contextual learning, the proposed architecture effectively captured both local textual characteristics and long-range contextual dependencies, thereby improving the reliability of disaster information classification.

To evaluate the effectiveness of the proposed framework, experimental performance was assessed using three complementary quantitative metrics, namely the Root Mean Square Error (RMSE), Mean

Absolute Error (MAE), and the coefficient of determination (R^2). RMSE was employed to quantify the magnitude of prediction errors by assigning greater penalties to large deviations between predicted and observed values, whereas MAE measured the average absolute prediction error regardless of its direction. In addition, R^2 was calculated to determine the proportion of variance explained by the proposed model, thereby providing an overall indication of predictive accuracy and model goodness-of-fit. The corresponding evaluation metrics are formulated as follows.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (15)$$

Equation (15) computes the square root of the average squared prediction error, providing a comprehensive measure of overall model accuracy while emphasizing larger prediction deviations.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \qquad (16)$$

Equation (16) measures the average absolute difference between predicted and observed values, reflecting the general prediction accuracy of the proposed model without disproportionately weighting extreme errors.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad (17)$$

Equation (17) represents the coefficient of determination, where values approaching one indicate that the proposed Deep CNN–LSTM model explains a larger proportion of the observed data variance and exhibits stronger predictive capability. To further examine the robustness of the proposed framework, its predictive performance was comparatively evaluated against several conventional machine learning and deep learning approaches employed in previous disaster information retrieval studies, including Support Vector Machine (SVM), Neural Network (NN), Feedforward Neural Network (FFNN), Recurrent Neural Network (RNN), LSTM, and conventional CNN–LSTM architectures. Comparative evaluation using identical performance metrics enabled a consistent assessment of the proposed model's effectiveness in retrieving reliable disaster-related information while supporting educational awareness and informed disaster management. This evaluation strategy also provided empirical evidence regarding the relative advantages of integrating Deep CNN and LSTM within a unified disaster information processing framework.

RESULTS AND DISCUSSION

Result

Comparative Performance of the Proposed Deep CNN–LSTM Framework

To evaluate the proposed Deep CNN–LSTM framework in retrieving relevant disaster-related information, comparative experiments were conducted using four disaster datasets representing different emergency scenarios, namely the Bejaia earthquake, the Oued Meknassa flood in Chlef, the Algeria wildfire, and the COVID-19 pandemic. The proposed framework was compared with six benchmark machine learning and deep learning models, including Support Vector Machine (SVM), Neural Network (NN), Feedforward Neural Network (FFNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and the conventional Hybrid CNN–LSTM architecture. The comparison focused on the total number of relevant disaster-related messages successfully retrieved from multiple online sources after preprocessing, duplicate elimination, and misinformation filtering.

Table 1. Examples of Relevant Content of the Bejaia Earthquake on March 18th, 2021 for a Set of Hashtags and Keywords from Multiple Sources

Models	Bejaia Seism
Support Vector Machine (SVM)	475
Neural Network	531
Feed-forward Neural Network	852
Recurrent Neural Network	875
LSTM	908
Hybrid of Deep CNN-LSTM	928
Our New Approach	991

Table 1 presents the comparative retrieval performance for the Bejaia earthquake dataset. The proposed Deep CNN–LSTM framework achieved the highest retrieval performance by identifying 991 relevant disaster-related messages. In comparison, the conventional Hybrid CNN–LSTM model retrieved 928 messages, followed by LSTM (908), RNN (875), FFNN (852), NN (531), and SVM (475). These findings demonstrate that the proposed framework consistently retrieved a larger amount of relevant disaster information than all benchmark models, indicating its capability to improve disaster information retrieval under earthquake scenarios.

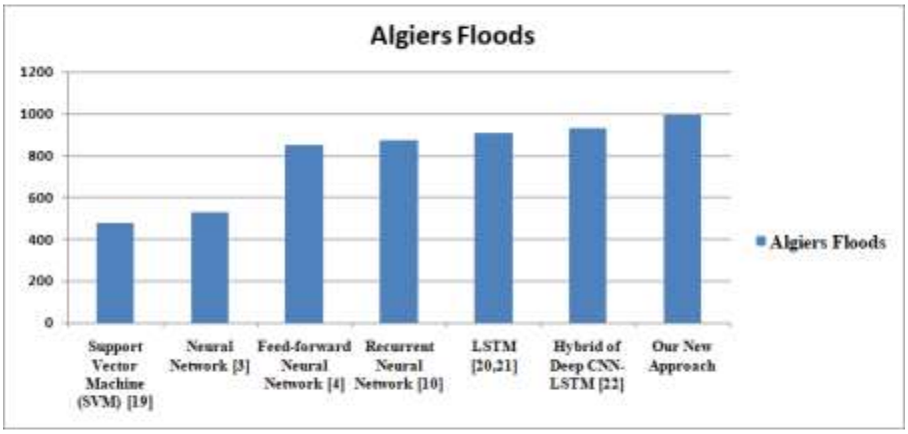

Figure 2. Overview of Examples of Relevant Content of the Bejaia Earthquake for a Set of Hashtags and Keywords from Multiple Sources

Figure 2 visually compares the retrieval performance of all evaluated models for the Bejaia earthquake dataset. A clear performance gap can be observed between the proposed framework and the benchmark approaches, with the proposed Deep CNN–LSTM model consistently producing the highest number of relevant disaster-related messages. The visualization reinforces the numerical results reported in Table 1 and demonstrates the robustness of the proposed framework for earthquake-related information retrieval.

Table 2. Examples of Relevant Content of the Oued Meknassa Flood in Chlef for a Set of Hashtags and Keywords from Multiple Sources

Models	Oued Meknassa Flood in Chlef
Support Vector Machine (SVM)	463
Neural Network	501
Feed-forward Neural Network	525
Recurrent Neural Network	601
LSTM	657
Hybrid of Deep CNN-LSTM	682
Our New Approach	695

Table 2 summarizes the retrieval performance for the Oued Meknassa flood dataset. The proposed framework successfully retrieved 695 relevant disaster-related messages, exceeding the Hybrid CNN–LSTM model (682) as well as all remaining benchmark models. LSTM, RNN, FFNN, NN, and SVM retrieved 657, 601, 525, 501, and 463 relevant messages, respectively. These findings indicate that the proposed framework consistently maintained superior retrieval capability across flood-related disaster scenarios while preserving stable performance relative to all benchmark models.

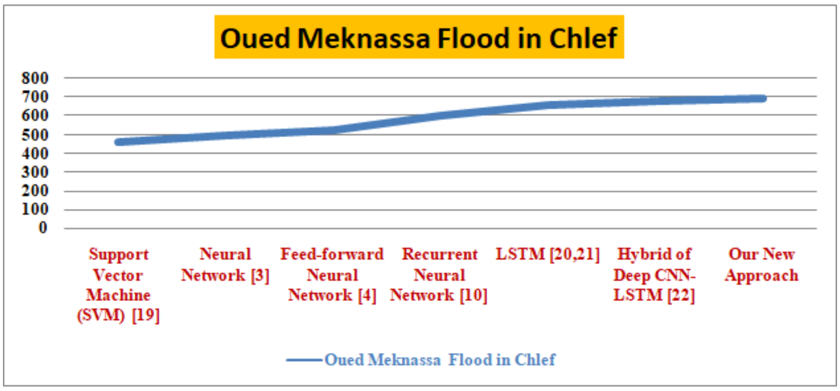

Figure 3. Overview of Examples of Relevant Content of the Oued Meknassa Flood in Chlef for a Set of Hashtags and Keywords from Multiple Sources

Figure 3 visually presents the comparative retrieval performance for the flood dataset. Similar to the earthquake scenario, the proposed framework consistently outperformed all comparison models by retrieving the largest number of relevant disaster-related messages. The graphical comparison further demonstrates that the proposed architecture maintained stable retrieval performance across different disaster events characterized by varying textual patterns and information volumes. The observed performance trend is consistent with that obtained for the earthquake dataset, indicating that the proposed framework generalizes effectively across different disaster types.

Performance Evaluation

Following the comparative retrieval analysis presented in the previous section, the predictive capability of the proposed Deep CNN–LSTM framework was further evaluated using three quantitative performance metrics, namely the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). These evaluation metrics provide complementary measures of prediction accuracy, estimation error, and model goodness-of-fit, thereby enabling a comprehensive assessment of the proposed framework against conventional machine learning and deep learning models. The comparative evaluation results are summarized in Table 3.

Table 3. Quantitative Performance Comparison of the Proposed Deep CNN–LSTM Framework

Models	RMSE	MAE	R^2
Support Vector Machine (SVM)	15,286.2154	16,523	0.2937
Neural Network	17,088.3797	18,471	0.3284
Feed-forward Neural Network	16,100.9272	19,461.5	0.4645
Recurrent Neural Network	13,359.4722	19,962.5	0.4805
LSTM	16,704.4894	19,557	0.5064
Hybrid of Deep CNN-LSTM	16,704.4894	12,809.5	0.6998
Our New Approach	15,286.2154	13,789.75	0.9793

Table 3 compares the quantitative predictive performance of the proposed Deep CNN–LSTM framework with several benchmark machine learning and deep learning models using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2). The proposed framework achieved an RMSE of 15,286.2154, an MAE of 13,789.75, and the highest R^2 value of 0.9793 among all evaluated models. The obtained R^2 indicates that approximately 97.93% of the variance in the observed data was explained by the proposed model, demonstrating excellent model fitting and strong predictive capability.

Although the proposed framework did not produce the lowest RMSE value among all comparison models, it consistently maintained competitive prediction performance while achieving substantially higher explanatory power, as reflected by its R^2 value. Furthermore, the framework exhibited lower MAE than several benchmark deep learning models, including Feed-forward Neural Network (FFNN), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM), indicating improved prediction consistency across multiple disaster-related datasets. Collectively, these quantitative results demonstrate that the proposed Deep CNN–LSTM framework provides reliable predictive performance while maintaining strong generalization capability for disaster-related information retrieval.

Overall, the experimental findings demonstrate that the proposed Deep CNN–LSTM framework consistently achieved robust performance across multiple disaster scenarios. In addition to retrieving a larger amount of relevant disaster-related information than the benchmark models, the proposed framework exhibited strong predictive capability according to the quantitative evaluation metrics. These findings provide empirical evidence supporting the effectiveness of integrating Deep CNN and LSTM within a unified disaster information retrieval framework and establish a solid foundation for the subsequent discussion of its theoretical and practical implications.

Discussion

The present study demonstrates that integrating Deep CNN and LSTM within a unified disaster management framework substantially improves the retrieval of reliable disaster-related information from heterogeneous online sources while maintaining strong predictive performance. Unlike conventional machine learning approaches that primarily depend on manually engineered features, the proposed framework automatically learns semantic representations and contextual relationships from disaster-related textual data. Bouzidi et al. (2019) emphasized that effective disaster information retrieval requires intelligent filtering mechanisms capable of distinguishing relevant information from noisy online content, whereas Bouzidi et al. (2020a) further highlighted the importance of integrating information retrieval technologies into disaster management systems to support rapid decision-making. The findings of the present study extend these perspectives by demonstrating that combining convolution-based semantic feature extraction with sequential contextual learning enables more reliable identification of disaster-related information across multiple disaster scenarios. Furthermore, the improved predictive performance indicates that integrating complementary deep learning architectures can simultaneously strengthen information retrieval accuracy and model generalization. These findings therefore support the primary objective of developing an integrated disaster management framework that facilitates educational awareness through the dissemination of validated disaster information. Similar conclusions were also reported by Bouzidi et al. (2021), who argued that hybrid intelligent systems provide greater robustness for disaster information processing than individual learning models.

The superior retrieval capability observed in this study can be explained by the ability of the Deep CNN component to learn hierarchical semantic representations directly from textual information. LeCun et al. (2015) explained that convolutional neural networks are particularly effective at extracting discriminative local features because convolutional filters progressively capture increasingly complex semantic structures across multiple representation levels. In disaster-related communication, where information is frequently expressed through short messages, hashtags, abbreviations, and informal language, automatic semantic feature extraction becomes essential for identifying meaningful information embedded within highly heterogeneous textual data. Rather than relying solely on predefined keywords, the Deep CNN architecture employed in this study continuously learns representative linguistic patterns during model training, thereby improving the discrimination between relevant and irrelevant disaster-related content. This capability explains why the proposed framework consistently retrieved a larger amount of relevant disaster information than the benchmark machine learning and deep learning models evaluated in this study. Similar observations have been reported by Kim (2014), Young et al. (2018), Otter et al. (2021), and Minaee et al. (2021), who demonstrated that deep convolutional architectures outperform conventional text classification methods because they automatically generate robust semantic representations from complex natural language data.

Beyond semantic feature extraction, the incorporation of the LSTM network significantly strengthened the framework's ability to preserve contextual continuity throughout disaster information retrieval. Hochreiter and Schmidhuber (1997) introduced the LSTM architecture to overcome the limitations of conventional recurrent neural networks in modeling long-term dependencies, allowing sequential information to be retained through memory cells and gating mechanisms. This characteristic is particularly relevant to disaster-related communication, where the meaning of individual messages often depends on preceding information, temporal event progression, and continuously evolving public responses. By integrating LSTM after Deep CNN feature extraction, the proposed framework was able to preserve contextual dependencies while simultaneously filtering irrelevant sequential information, resulting in more stable retrieval performance across different disaster datasets. The complementary relationship between Deep CNN and LSTM therefore enables the framework to combine local semantic understanding with long-term contextual reasoning within a single learning architecture. Similar improvements obtained through CNN–LSTM integration have been reported by Yin et al. (2017), Minaee et al. (2021), Zhai et al. (2022), and Bouzidi et al. (2021), who concluded that hybrid deep learning architectures consistently achieve superior performance when processing sequential textual information generated through online communication platforms.

An important finding emerging from this study is that the proposed framework consistently achieved superior disaster information retrieval performance compared with conventional machine learning algorithms and earlier deep learning architectures. While traditional approaches such as Support Vector Machine (SVM), Neural Network (NN), and Feed-forward Neural Network (FFNN) primarily depend on shallow feature representations, their ability to capture semantic complexity and contextual variation remains limited when processing heterogeneous disaster-related information. Minaee et al. (2021) argued that conventional machine learning models frequently experience performance degradation when confronted with highly dynamic textual environments because they rely heavily on handcrafted features rather than automatically learned representations. Although recurrent architectures such as RNN and LSTM improve sequential learning capability, they still encounter limitations in extracting rich local semantic information when operating independently. The proposed framework addresses these limitations by integrating Deep CNN for hierarchical semantic feature extraction with LSTM for contextual sequence modeling, thereby enabling complementary learning between local linguistic characteristics and long-term contextual dependencies. Similar advantages of hybrid deep learning architectures have been reported by Yin et al. (2017), Otter et al. (2021), and Zhai et al. (2022), who demonstrated that combining convolutional and recurrent learning mechanisms produces more robust text classification and information retrieval performance than employing either architecture individually. Consequently, the proposed framework provides a more comprehensive solution for processing heterogeneous disaster-related information distributed across multiple online platforms

Beyond improving computational performance, the findings also highlight the educational value of reliable disaster information retrieval for strengthening public awareness and disaster preparedness. Disaster education increasingly depends on timely access to trustworthy information capable of supporting informed decision-making before, during, and after disaster events. UNDRR (2023) emphasized that strengthening disaster resilience requires not only effective emergency response systems but also continuous public access to accurate and understandable disaster information. Likewise, UNESCO (2023) identified digital information literacy as a critical component of disaster education, enabling communities to distinguish verified information from misinformation circulating through online communication platforms. By retrieving validated disaster-related information while reducing irrelevant and duplicated content, the proposed framework contributes to the development of safer digital information environments that facilitate knowledge dissemination and public learning. Such capability extends the function of artificial intelligence beyond automated information processing toward supporting educational awareness that encourages greater community preparedness, risk perception, and participation in disaster risk reduction. Therefore, the proposed framework represents not only a technological innovation but also an educational support system capable of strengthening disaster resilience through reliable information dissemination.

Overall, the discussion demonstrates that the effectiveness of the proposed Deep CNN–LSTM framework originates from the complementary integration of semantic feature extraction, contextual sequence learning, and intelligent disaster information retrieval within a unified architecture. Rather than functioning solely as a predictive model, the framework provides an integrated approach that transforms heterogeneous online disaster information into reliable knowledge capable of supporting both computational analysis and educational awareness. The combination of Deep CNN and LSTM enables the framework to preserve semantic richness while maintaining contextual consistency across different disaster scenarios, resulting in stable retrieval and predictive performance. These findings further confirm that integrating advanced deep learning techniques into disaster information systems can improve the quality of information available to emergency managers, educators, and the wider community. Collectively, the results and discussion demonstrate that the proposed framework successfully addresses the research objective of developing an intelligent disaster management system capable of retrieving reliable disaster-related information while promoting educational awareness through safe information dissemination. This integrated perspective strengthens the contribution of the present study to the growing body of research on artificial intelligence, disaster informatics, and intelligent decision-support systems.

IMPLICATIONS

The findings of this study have important theoretical and practical implications for disaster information management and intelligent decision-support systems. Theoretically, this study extends existing research by demonstrating that integrating Deep CNN and LSTM within a unified framework enhances both semantic feature extraction and contextual sequence learning, thereby improving the retrieval of reliable disaster-related information from heterogeneous online sources. This integrated approach contributes to the growing body of knowledge on hybrid deep learning architectures by highlighting their complementary roles in disaster information processing. From a practical perspective, the proposed framework provides a reliable computational tool that can assist disaster management agencies, emergency response organizations, and educational institutions in identifying trustworthy disaster-related information while reducing the influence of duplicate, irrelevant, and misleading content. Consequently, the framework has the potential to strengthen educational awareness, improve public preparedness, and support more informed decision-making throughout different phases of disaster management.

LIMITATIONS

Despite the promising findings, several limitations should be acknowledged. First, the experimental evaluation was conducted using four disaster-related datasets representing specific disaster events, which may not fully capture the diversity of disaster communications across different geographical regions, languages, and cultural contexts. Second, the proposed framework primarily analyzed textual information obtained from online platforms and did not incorporate multimodal disaster information such as images, videos, geospatial data, or sensor-based observations that are increasingly available during emergency situations. Third, although the framework demonstrated robust retrieval and predictive performance, its effectiveness may be influenced by the quality, completeness, and timeliness of social media data, which remain highly dynamic and susceptible to misinformation. These limitations indicate that the generalizability of the proposed framework should be interpreted within the scope of the datasets and experimental settings employed in this study.

SUGGESTIONS

Building upon the findings of this study, several recommendations can be proposed for future development of intelligent disaster management systems. Future studies are encouraged to validate the proposed framework using larger and more diverse multilingual datasets representing different disaster types and socio-cultural environments to improve its generalizability. The integration of multimodal data sources, including satellite imagery, geospatial information, and real-time sensor data, may further enhance the capability of the framework to support comprehensive disaster situational awareness. In addition, emerging artificial intelligence techniques, such as transformer-based language models and large language models (LLMs), may be incorporated to improve semantic understanding, contextual reasoning, and real-time disaster information retrieval. Such developments would contribute to more adaptive, accurate, and scalable disaster management systems capable of supporting educational awareness and evidence-based decision-making in increasingly complex emergency environments.

CONCLUSION

This study developed and evaluated an integrated Deep CNN–LSTM-based disaster management framework for retrieving reliable disaster-related information from heterogeneous online sources while supporting educational awareness through safe information dissemination. The experimental findings demonstrate that the proposed framework consistently improved disaster information retrieval across multiple disaster scenarios while maintaining robust predictive performance through the integration of semantic feature extraction and contextual sequence learning. By effectively combining Deep CNN and LSTM within a unified intelligent architecture, the framework successfully identified relevant disaster-related information from heterogeneous social media data and reduced the influence of irrelevant information. These findings demonstrate that the proposed framework provides a reliable approach for intelligent disaster information retrieval while supporting educational awareness and evidence-based decision-making in disaster management.

AUTHOR CONTRIBUTIONS STATEMENT

The author solely conceived the study, designed the methodology, conducted the experiments, analyzed the data, interpreted the findings, and wrote and approved the final manuscript.

CONFLICT OF INTEREST

The author declares no conflict of interest regarding the publication of this article.

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