ORIGINAL RESEARCH

Enhancing Warning, Situational Awareness, Assessment and Education in Managing Emergency: Case Study of COVID-19

Zair Bouzidi[1,2] · Mourad Amad[1] · Abdelmalek Boudries[2]

Abstract

The volume of network and Internet traffic is increasing extraordinarily fast daily, creating huge data. With this volume, variety, speed, and precision of data, it is hard to collect crisis information in such a massive data environment. This paper proposes a hybrid of deep convolutional neural network (CNN)-long short-term memory (LSTM)-based model to efficiently retrieve crisis information. Deep CNN is used to extract significant characteristics from multiple sources. LSTM is used to maintain long-term dependencies in extracted characteristics while preventing overfitting on recurring connections. This method has been compared to previous approaches to the performance of a publicly available dataset to demonstrate its highly satisfactory performance. This new approach allows integrating artificial intelligence technologies, deep learning and social media in managing crisis model. It is based on an extension of our previous approach namely long short-term memory-based disaster management and education: this experience forms a background for this model. It combines representation training with situational awareness and education, while retrieving template information by combining various search results from multiple sources. We have extended it to improve our managing disaster model and evaluate it in the case of the coronavirus disease 2019 (COVID-19) while achieving promising results.

Keywords Alert · Assessment · Awareness · Deep CNN-LSTM · Education · Social media

Introduction

The use of social networks in crisis situations to timely share information [1] has become common practice in recent years. With the proliferation of social media, an ongoing event [2] is being discussed on all these channels with generally qualitative and significative differences [3, 4] in the information obtained. To get a complete event view, it is important to collect contents [4] from various sources. However, the challenges that managers face are enormous when it comes to retrieving content shared on the Web [5], with good, excellent and sharp situational awareness.

Several automated systems [3–5] have been designed to help managers identify and filter useful information posted on the Web. Most of the work, has focused on using social network (only on Twitter) as a source of information and only, on a few managing disaster phases [1, 2, 5], but few are, concurrently, dedicated to warning [3], education [4] and situational awareness. The design of managing emergency systems using various information sources (the Web), and dedicated entirely to warning, situational awareness and education, is a challenge.

Research on extracting content from social media can be considered as sequence learning problem [6, 7]. Thus, we propose a new approach of managing emergency model, based on a hybrid of deep convolutional neural network with long short-term memory network used thanks to its ability of learning long-term dependencies. This new approach allows integrating artificial intelligence technologies, deep learning

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and social media, in the managing crisis model [7]. This is based on an extension of our previous approach [4, 8]: this experience forms the background for this model. It combines representation training with alert, situational awareness and education, while integrating encapsulations from various sources and retrieving information by combining various search results, providing some good ideas for its extending to improve managing emergency.

In this article, we try to identify relevant content related to the upcoming disaster event. Once this information is retrieved and cleaned of non-informative information, it can be used to update information (warning, situational awareness or education) of managers to make quick and effective decisions that could help people in need or to save lives. Thus, we provide, not only, a solution to this challenge, but also, to achieve promising results.

Our study has fourfold main contributions.

1. We develop a recurrent neural network-based model that uses low-level capabilities of content learning of various sources (the Web) to automatically and efficiently collect real-time reports of situation awareness distributed during large scale catastrophic events, to automatically separate relevant content from non-informative information.
2. Using a dataset of keywords/hashtags related to various natural or anthropogenic catastrophic events, this model collects, according to their lexical similarity, relevant contents relating to various catastrophic events.
3. We develop an event-independent model to filter content on various sources at a time in the future events, while keeping in mind the limitations of previous work and outperforming all the others.
4. Finally, we tested it immediately on the global coronavirus pandemic, called COVID-19 by the World Health Organization (WHO), since January 2020, until nowadays. Then, we conclude, in giving some perspectives.

The paper rest is structured as follows. The next section provides background and related works. The third section introduces our new model, namely the hybrid of deep CNN-LSTM. We modeled it, providing details on warning, situational awareness and disaster education of imminence or impact disaster and preliminary results, with a discussion about the results obtained. Then, we conclude, giving some perspectives.

Background and Related Works

Online messages contain important information [9] that can also be helpful in making quick decisions to help the affected community if they are dealt with quickly

Table 1 Latest catastrophic events

No	Catastrophic event	Period	Damage
1	Volcanic eruption of Tambora in 1815	1815	92,000
2	China Floods	1931	200,000
2	Avalanche from Mount Huascaran	1970	75,000
4	Forest fire Haiti	Oct 2007	230,000 and 220,000
5	Tsunami in the Indian Ocean	2004	250,000
6	Haiti earthquake	2010	200,000

and effectively. Many types of processing techniques ranging from comparable document-aligned data [5], statistical analysis, natural language processing [10] to machine learning [1, 3, 4] to computational linguistics [11] have been developed for different purposes, without, fully exploiting this data, despite the existence of some resources, such as annotated data and standardized lexical resources.

Most event detection methods are based on keywords/hashtags used in tweets during catastrophic events to classify messages as real-time event reports, using a support vector machine (SVM).

Rogstadius et al. [12] were able to capture distributed situation awareness reports based on Twitter activity during natural disasters. Table 1 gives an overview of recent natural and anthropogenic disasters, and all their damage assessment.

COVID-19 is a pandemic of an evoluting infectious disease. It first appears in China, in November 2019 and spreads worldwide. Essential protective measures have been taken to prevent the saturation of intensive care services and strengthen preventive hygiene. This global pandemic has prompted the cancelation of many sporting and cultural events around the world, the adoption of containment measures by several countries to postpone the creation of new centers of contagion, the closing of several countries' borders, and a stock market crash as a result of the uncertainty and concerns it has created for the global economy. It also has effects in terms of social and economic instability and is the pretext for the online dissemination of erroneous or conspiracy theory information. Luckily, with approximately 2% of the cases detected, the provisional death rate is lower than in previous coronavirus epidemics. About roughly 110,270,288 cumulative cases were confirmed globally as of February 19th, 2021, including 62,077,509 individuals healed and 2,439,834 dead. The contaminations number with the COVID-19 coronavirus continues to increase to this day. More than 4000 variants of the virus, called SARS-CoV-2 according to International Committee on Taxonomy of Viruses, have been identified around the world: a natural

process as the virus acquires mutations over time to ensure its survival.

British variant or B.1.1.7 (called VOC 202012/01 or B.1.1.7)[1] : 64% more lethal. It was reported by United Kingdom (UK) authorities on December 14th, 2020 with a sharp increase in cases on the island. Not only is it more contagious, it is also 64% more deadly than the classic coronavirus.

South African variant (called 501Y.V2): 50% more transmissible. It is 1.5 times more contagious than SARS-CoV-2, but not more lethal. However, it tends to show that people infected with the South African variant of the new coronavirus have better immunity to other mutations in the virus.

Two Brazilian variants from the Amazon: the first variant, B1.1.248, was detected in Japan in a family from the Amazon (Brazil) and a second, called P.1. It is also more likely to cause death.

We suggest a new emergency management model focused on recurrent neural networks for warning, situational awareness, and education on social networks in this paper. It is based on an extension of recurrent neural network (RNN) [8] of our previous approach used to improve fraud detection and time series forecasting. This last work is based on the feedforward neural network (FFNN) [4] used in our previous works for disaster management and disaster education. This experience forms a background for this emergency management model, based on a hybrid of deep CNN-LSTM. This emergency management model combines representation training with warning, situational awareness and disaster education, while integrating encapsulations from multiple sources and retrieving information by combining multiple search results (all the Web).

Messenger, Facebook, Twitter, Viber and so on are platforms where people express emotions. The data available on social networks differ in many ways from other Web sources (press articles, for example).

Contents are less formal, contain words from more than one language, have various grammatical and spelling errors, while being, for the most part, unstructured, fuzzy and short-lived [3, 4]. Their length and content vary considerably [17]. We detected emotions using features, such as interjections, blasphemy, emoticons and the general feeling of the message. These are widely used by to convey emotions as: danger, surprise, happiness, etc.

Our emergency management model based on a real-time hybrid of deep CNN-LSTM is best suited to situational awareness (see Table 2). It uses Multisource content (from all websites) (see Table 3) with training opportunities for automatic and effectively capturing the situation in real-time

Table 2 Overview of the most important floods and their damage (deaths) since 2001 in Algeria

Situational awareness approaches	Identification methods
[12]	CrisisTracker: Crowdsourced Twitter curation for disaster awareness
[13]	Summarizing with social-temporal context
[14]	Analysis of Twitter activities in Hurricane Sandy
[15]	Building an abstract of Tweet dataset
[16]	Semi-automated classifier based on artificial intelligence for disaster response
Our new approach	Based on hybrid of deep CNN-LSTM

reports during catastrophic events in large scale, using keywords/hashtags and tagged content. It collects the messages according to their lexical similarity, related to various catastrophic events, using disaster education (see Table 4).

The content was captured from online channels followed by the online tool Radian6 [17]. Actually, many networking platforms enable access to their content by Application Programming Interface (API) [17]. Online listening tools serve as a model for collecting content, cleaning it up from non-informative information, enabling relevance through the learning corpus using tagged messages, and analyzing results for alert, situational awareness and disaster education.

New Model of Emergency Management

We present our new network model, based on a hybrid of deep CNN-LSTM, according to Abiodun et al. [22]. The LSTM layer has been shown to be powerful in handling temporal correlation. Its extension has convolutional structures in both input-state and state-to-state transitions will solve this problem. By stacking multiple CNN-LSTM layers and building a coding prediction structure, we created a network model for these space-time sequence prediction problems.

The crisis forecasting goal consists of using the previously sequence of observed social networking to prevent an event in a local region, as Algiers, London, or Paris. From automated learning perspective, this is a problem of predicting space-time sequences.

Suppose we have a dynamic system represented by an (MxN) grid with M rows and N columns. In each cell of the grid, there are P measures (word, bias) varying in time. At any time, the observation can be represented by a tensor X belonging to R^{PxMxN}, with R denoting the domain of observed traits. With recording periodically observations, we will have a sequence of tensors $X_1, X_2, ..., X_t$. Spatio-time sequence prediction predicts the most probable sequence of length K, given previous J observations (including the current sequence) formulated by the following Eq. (1):

Table 3 Comparative table of all techniques and OSN used

References	Identification methods	Used OSN
[18]	Learning based on Flood Game	Twitter
[19]	Educational purposes	Twitter
[13]	Summarizing with social-temporal context	Twitter
[15]	Build an abstract of Tweet dataset	Twitter
[16]	Semi-automated classifier based on artificial intelligence for disaster response	Twitter
[3]	Based on artificial neural network (ANN)	Twitter and Facebook
[4]	Feedforward neural network (FFNN)	The Web
[8]	Recurrent neural network (RNN)	The Web
[20, 21]	LSTM	The Web
Our new approach	Hybrid of deep CNN-LSTM	The Web

Table 4 Comparative table of all techniques used with education

Disaster education approach	Methods
[18]	Learning based on Flood Game
[19]	Educational purposes
[4]	Based on feedforward neural network (FFNN)
[21]	Based on LSTM (LSTM)
Our new approach	Based on a hybrid of deep CNN-LSTM

$$\hat{Y}_{t+1}, \cdots, \hat{Y}_{t+K} = \arg \max_{X_{t+1}, \cdots, X_{t+K}} p(X_{t+1}, \cdots, X_{t+K} \mid Y_{t-J+1}, \cdots, Y_{t-J+K}) \tag{1}$$

Observing at each time stamp is a 2D map. In dividing this map into non-tiled, non-overlapping patches and visualizing pixels inside a patch as its measurements (see Fig. 1 with the functioning of the hybrid of deep CNN-LSTM model), the problem is naturally a spatio-time sequence prediction. This spatio-time sequence prediction problem is different from that of one-step time series prediction because this prediction target contains both spatial and temporal structures.

A content **e**, denoting the input to the network, is defined as the following Eq. (2):

$$e = (w_1, ..., w_i, ..., w_n) \tag{2}$$

containing words $w_i \in W$, each coming from a finite vocabulary V. C^n is the set of contents issued from the social media.

For the error functionality: if $y = 1$, $p(x)$ must be the greatest. Thus, the error is defined as the following eq. (3):

$$-\ln(p(x)) \tag{3}$$

Symmetrically, $p(x)$ must be as small, if $y = 0$. The error is then formulated by the following Eq. (4):

$$-\ln(1 - p(x)) \tag{4}$$

Therefore, the general formula is defined by the following Eq. (5):

$$error = -y * \ln(p(x)) - (1 - y) * \ln(1 - p(x)) \tag{5}$$

Once an error function defined, the problem (of learning) becomes an optimization: find the coefficient vector w^* minimizing the error. In logistic regression, the error function is convex and this vector is unique.

Once the optimum w^* coefficient vector determined, a classifier is available to classify. It is necessary to have an independent test set for estimating the classifier error probability.

CNNs (see Fig. 2) are regularized variants of multilayer perceptrons (each neuron is linked to the next layer) [23]. The *fully connectedness* makes them susceptible to overfitting information, as the following Eq. (6):

$$\forall n \in [1, 2n_c^{[l]}]$$

$$\text{Conv}(a^{[l-1]}, K_{x,y}^{(n)}) = \phi^{[l]} \left(\sum_{i=1}^{n_H^{[l-1]}} \sum_{j=1}^{n_W^{[l-1]}} \sum_{k=1}^{n_C^{[l-1]}} K_{i,j,k}^{(a)} * a_{x+i-1,y+j-1,k}^{[l-1]} * b_n^{[l]} \right) \tag{6}$$

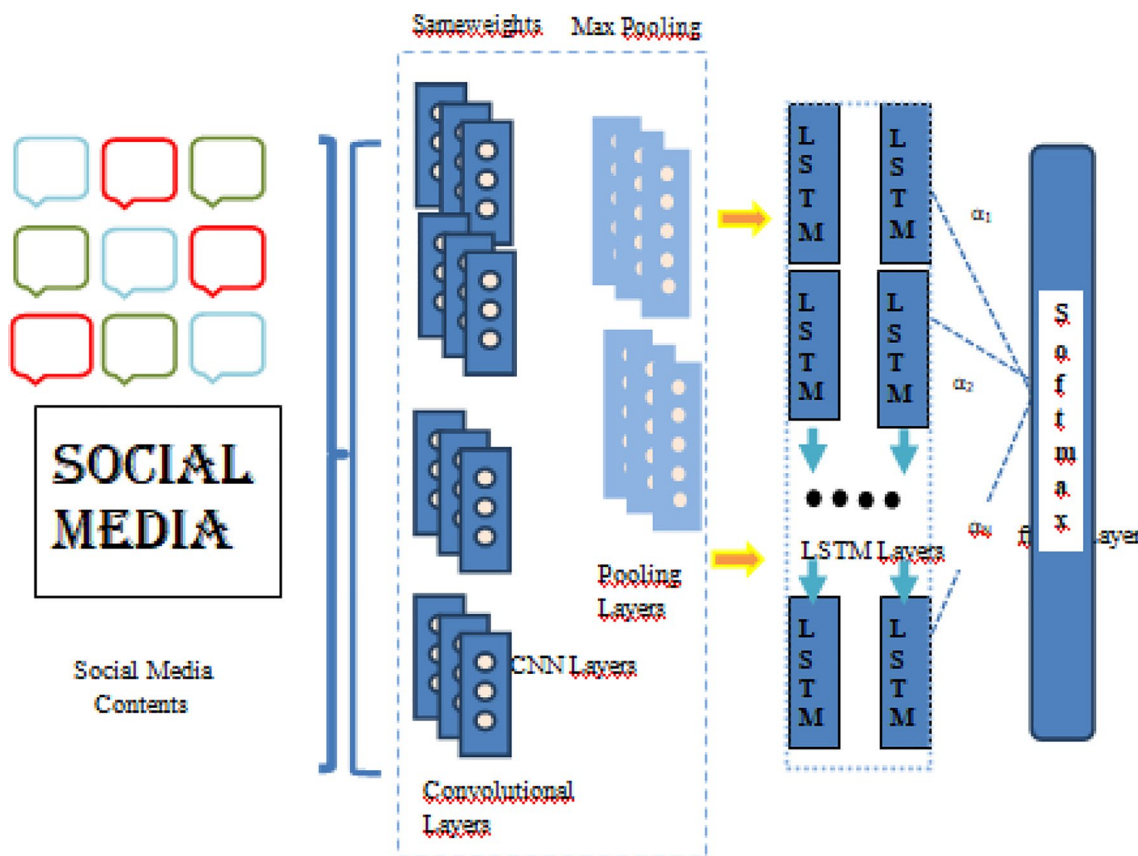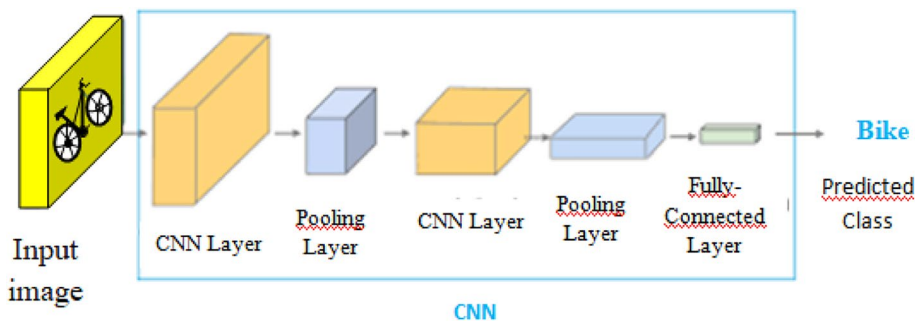$$\text{Dim}(\text{Conv}(a^{[l-1]}, K^{(n)}) = (n_H^{[l]}, n_W^{[l]})$$

Fig. 1 Functioning of the hybrid of deep CNN-LSTM-based emergency management

Fig. 2 The convolutional neural network

CNNs use very little preprocessing: they learn the filters, hand-engineered in conventional algorithms. The formula for the current state is formulated by the following Eq. (7):

$$h_t = f(h_{t-1}, x_t) \tag{7}$$

Applying activation function **tanh**, we have the following Eq. (8):

$$h_t = \tanh(\sigma_{hh} * h_{t-1} + \sigma_{x_h} * x_t) \tag{8}$$

where σ is weight. h denotes the single hidden vector. σ_{hh} is the previous hidden state weight, σ_{xh} the current

input-state weight and tanh the function of activation, that introduces a non-linearity squashing the activations to the range $[-1,1]$.

Output is formulated by the following Eq. (9):

$$y_t = \sigma_{hy} * h_t \tag{9}$$

where y_t is the output state. σ_{hy} denotes the weight at the output state.

At each time step, all calculations necessary on the forward pass are given by the following Eqs. (10) and (11):
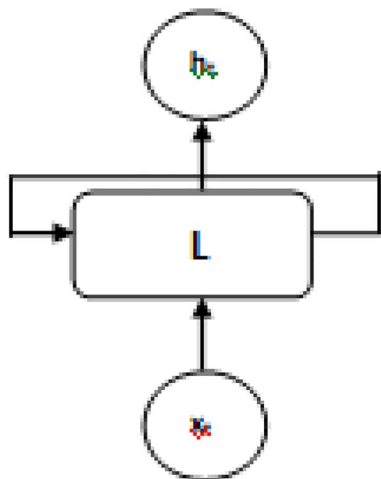
Fig. 3 Overview of LSTM, its gates and activation functions

$$h_t = \alpha(\sigma_{hx} * x_t + \sigma_{hh}.h_{t-1} + b_h) \tag{10}$$

$$y_t = \beta(\sigma_{yh} * h_t + b_y) \tag{11}$$

where σ_{hx} is the matrix of weights between the input and hidden layers. b_h is hidden bias vector. α denotes the hidden layer function. α is usually an element-wise application of a sigmoid function and β is the output layer function.

LSTM introduces the memory cell [24]. LSTM networks, a kind of sophisticated RNN, using specific units, help to remember past data in memory cell, keeping information for a long time. This solves RNN gradient disappearance question. In training the model using backpropagation, LSTM is well suited to classify, process and forecast time series, thanks to time lags of unknown length (see Fig. 3). LSTM model can be described as follows:

1. Input gate—find input value to use to change the memory. **Sigmoid** chooses values from 0,1 to pass and **tanh** gives weight to the values transferred from − 1 to 1, according to their significance level. Three gates are present and given by the following Eqs. (12) and (13):

$$i_t = \sigma(\omega_{ix} * x_t + \omega_{ih} * h_{t-1} + b_i) \tag{12}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(\omega_{cx} * x_t + \omega_{ch} * h_{t-1} + b_c) \tag{13}$$

2. Forget gate—using sigmoid, find information to delete from the block. It analyses, for each number in cell state c_{t-1}, the previous state h_{t-1} and material input x_t, selecting 0 to omit it or 1 to keep it, as given by the following Eq. (14):

$$f_t = \sigma(\omega_{fx} * x_t + \omega_{fh} * h_{t-1} + b_f) \tag{14}$$

3. Output gate—to select the output, the input and block memory are used. The sigmoid function selects values to pass 0,1 and the tanh function gives weight to the values transferred, evaluating their degree of significance varying from − 1 to 1 and multiplied by the sigmoid output, as given by the following Eqs. (15) and (16):

$$j_t = \sigma(\omega_{jx} * x_t + \omega_{jh} * h_{t-1} + b_j) \tag{15}$$

$$h_t = j_t \odot \tanh(c_t) \tag{16}$$

where $\odot$ denotes multiplication of element-wise. ω is the function of logistic sigmoid. i, f and j are, respectively, input, forget and output gate. c is cell activation vector, same size as the hidden vector h in level k.

With the sigmoid [25], we have the following Eq. (17):

$$\phi(x) = \frac{1}{1 + e^{-x}} \tag{17}$$

and tanh [26], we have the following Eq. (18):

$$\tanh(x) = \frac{1 - -e^{-2x}}{1 + e^{-2x}}. \tag{18}$$

Proposed Hybrid of Deep CNN-LSTM-based Emergency Management Model

The entire hybrid of deep CNN-LSTM modeling procedure has been studied with the aim of introducing methods leading to always efficient model. It consists of learning, preprocessing and post-processing of data, various types of initializing weights and algorithms for learning, activation and error functions. Besides, all of these affect its performance, but increased attention was focused on finding the best architecture.

Foundation of the Hybrid of Deep CNN-LSTM Model

We have a hybrid of deep CNN-LSTM with hidden layers taking as input contents formulated by the following Eq. (19):

$$e = (w_1, ..., w_i, ..., w_n) \tag{19}$$

containing words W, each coming from a finite vocabulary **V**, that is the set of contents issued from the social media and gives as output the relevant content e_k. Let the following Eq. (20) be

$$\forall \quad i \in [1, N] \qquad e_i \in C^n = E$$

$$\& \qquad e_i = (w_{i1}, w_{i2}, ..., w_{in}) \tag{20}$$

containing words each coming from the set of words **W**. Each word built from a finite vocabulary **V**, the incorporation
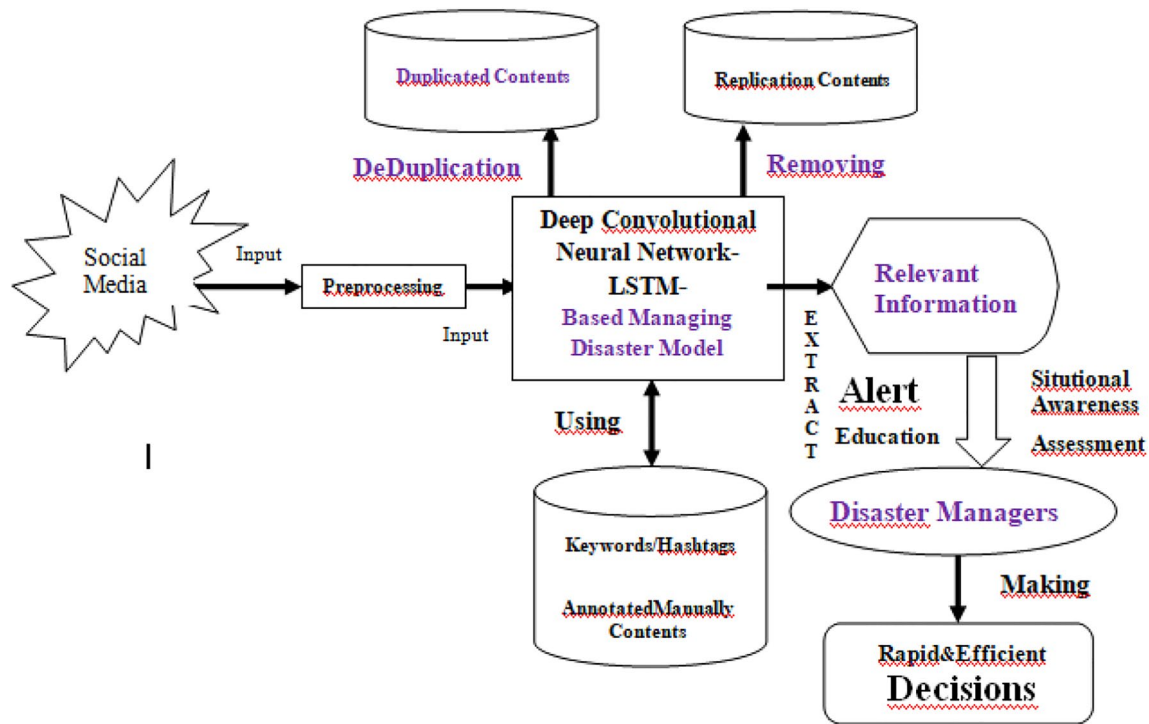
Fig. 4 Architecture of the hybrid of deep CNN-LSTM-based emergency management

of a content of the source message i relevant for, at least, a keyword or a hashtag as

$$\exists j \in [1,M] \quad such \ as \quad h_j \in H$$

We want to learn a generic space such as formulated by the following Eq. (21):

$$E_K = \max_{k \in [1,K]} \left\{ e_k \right\} \qquad (21)$$

normalizing the differences the following Eq. (22):

$$E_K = [E - RDF] \quad where \quad RDF = [R + D + F] \qquad (22)$$

where R, D and F denote, respectively, the set of duplicate re-tweets, duplicate contents and false alerts.

The hybrid of deep CNN-LSTM can explain the transformation of e_i into e_k by the following Eq. (23):

$$\exists \quad j \in [1,M] \quad | \quad h_j \in H$$
$$\& \quad \exists \quad l \in [1,L] \quad | \quad w_l \in W \quad /$$

$$\max_{k \in [1,K]} \left\{ e_i \rightarrow e_k = \left\{ e_i | e_i \ is \ relevant \ for \ h_j \ \& \ w_l \right\} \right\} \qquad (23)$$

$$with \quad i \in [1,N] \Big\}$$

and $e_i \notin [R + D + F]$

where R, D and F denote, respectively, the set of duplicate re-tweets, duplicate contents and false alerts.

Transforming e_i into e_k can be described, with the automated learning, by the following Eq. (24):

$$\exists j \in [1,M] \quad | \quad h_j \in H \quad \& \quad \exists l \in [1,L] \quad | \quad w_l \in W/$$

$$\max_{k \in [1,K]} \left\{ e_i \longrightarrow e_k = \{ e_i \quad / \quad e_i \quad Relevant \quad for \quad (h_j \ , \ w_l) \} \right\} \qquad (24)$$

$$with \quad i \in [1,N] \quad \& \quad e_i \notin [R + D + F]$$

where R, D and F denote, respectively, the set of duplicate re-tweets, duplicate contents and false alerts.

The objective is then to maximize the size K of E_K set. Fig. 4 shows the architecture of the hybrid of deep CNN-LSTM-based emergency management.

Figure 5 shows example of the relevant contents obtained from social media thanks to the hybrid of deep CNN-LSTM-based emergency management.

Warning and Alert

Social media data help respond to disasters [14]. During crisis events, citizens easily turn to social networks to confide in, quickly disseminate information and learn useful insights. Social media improve people's knowledge of the situation, facilitate the dissemination of information (especially in emergencies), enable for learning useful insights, early warning and helping coordinate relief efforts. Besides, the spatio-temporal dissemination of messages relating to crises facilitates real-time monitoring and evaluating disasters, before, during and after events [14].

Most disaster publications assume that the media are the most important mitigation tool for managers because their content creates awareness. Victims, as well as volunteers or relief organizations increasingly use social media to act on high-profile events [12]. Researchers show correlation between per capita social media activity and disaster damage, facilitating rapid assessment [14].

The training data are created from COVID-19. This information, easily obtained using the neural network, is manually annotated by volunteers.

Situational Awareness

In crisis situations, the essential decision making needed depends heavily on the availability, quality, and timeliness of relevant information available to decision-makers. Our approach in designing situational awareness systems is to design warning model that consider situations and events as fundamental entities. An important aspect of emergency situation awareness using social media consists of being the first to detect and characterize the emergency-related event. Thus, we will be better equipped to take all the precautions and the luck on our side. In the evolving pandemic, knowing and especially applying, first of all, wearing the bib and making physical/social distance, will play a significant role in saving lives. This will serve as first operations, among others, to apply. Situational awareness and disaster education influenced significantly physical/social distancing [27]. Thus, increasing situational awareness, in times of public health crisis, using education, enables significantly increasing protective health behavior adoption and containing the infectious diseases spread.

Assessment

Several tools for statistics and artificial intelligence are used with large data analysis techniques and recently data smart streaming, as the discovering process of new knowledge by analyzing large quantities of data, in streaming,

Table 5 COVID-19 damage assessment: overview of the COVID-19 and their damage (affected, dead and healed) since May 31st, 2020, in Algeria

	Affected	Death	Healed
May 31st, 2020	9394	653	
June 6th, 2020	1005	698	
July 21st, 2020	24,278	11	
August 24th, 2020	41,858	1446	
October 1st, 2020	52,658	1783	36,958
November 10th, 2020	63,446	2077	42,626
November 12th, 2020	64,257	2093	42,980
March 16th, 2021	115,410	3040	79,994

using deep learning as well as statistical and mathematical techniques.

Wildfires raging in northern Algeria have killed about 90 people since Monday, August 9th, have still not been extinguished on Saturday, August 14th, 2021. Besides, these wildfires are extremely intensified by the heat. Wildfires affect, every year, the country north. In 2020, 44,000 hectares of coppice were burnt. Wildfires, increased over the globe, are associated with various phenomena that are anticipated by scientists due to global warming.

Reliable connectivity and data security allow us to offer seamless, efficient services for remote control and surveillance of fire detection and alarm systems. Remote services transform our aid into a state-of-the-art IoT solution. It permits remote access to fire alarm tools for manipulating, maintenance and live monitoring of pollution level of fire detectors and alarm, and trouble transmissions to smart devices. Table 5 is an example of assessment of coronavirus COVID-19.

Disaster Education

This model is intended to support an introductory emergency management internship for citizens, interns and future disaster managers. Education tool is used in three modes [4]. Novice mode enables the trainee using complete automated design and learning tools set, as observing various programs at work, experimenting them. It enables, to trainee, gradually learning from his experience, observations and mistakes. Beginners mode enables him, at any point, to ask education tool to generate the next step. This tool analyzes knowledge of this step and provides both the optimal option and a list of all relevant stages. If the trainee is not satisfied with the optimal operation suggested by the system, he can

choose himself any appropriate operation. At any time, the online manual rehearsal mode enables the trainee accessing to all previous courses by: reviewing any previously learned concept, restarting any previously learned example and resuming any case learned. This mode provides access to all learned items for reference and, therefore, supports sample-based online help. Educational messages play a role in increasing situational awareness [27] during public health crises.

The COVID-19 pandemic is an emerging infectious disease [28]. Disaster education for the COVID-19 pandemic involves consists of advising to always strengthen preventive hygiene, namely elimination of physical contact, kisses and handshakes, coughing and/or sneezing into the crook of the elbow, using disposable tissues, taking physical/social distancing, wearing a bib, end of gatherings and major events as well as unnecessary trips, promotion of hand washing and avoiding any social or cultural regrouping. But above all, this disaster education consists of constantly rehashing this advice on all information channels, websites and all social and networking media to have as much situational awareness as possible.

New educational programs have been designed and adapted by many academic institutions in collaboration with hospitals, professional organizations, governmental and nongovernmental organizations to support internships aimed at preparing health personnel and system to meet affected populations health needs. It serves for developing the *core competencies* of essential knowledge and skills for disaster health workers for efficiently standardizing good health practices in order to overcome any new health crisis. Disaster healthcare personnel was developed and endorsed by governmental and professional organizations and societies [29].

Experimental Results

In this section, we present the experiments carried out to compare the performance of deep learning models, including our proposed hybrid model, tested with the dataset, introduced in the following subsection, which have been preprocessed. The mean squared error (RMSE), the mean absolute error (MAE) and the mean square error (MSE) were the measures used to assess model performance across all experiments. Since the F score is derived from recall and precision, we also show these two measures for reference. The results are presented, discussed and analyzed in the following sections.

Evaluation Criteria

An excellent alert template is needed to collect messages from a possible disaster. To verify the performance of the

Table 6 Examples of relevant content of COVID-19 for a hashtags' and keywords' set from social media

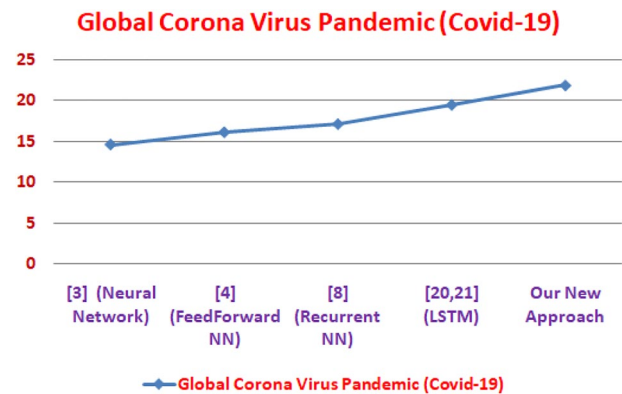| Model	RMSE	MAE	R^2
(Neural network) [3]	17,088.3797	18,471	0.3284
(Feedforward NN) [4]	16,100.9272	19,461.5	0.4645
(Recurrent NN) [8]	13,359.4722	19,962.5	0.4805
(LSTM) [20, 21]	16,704.4894	19,557	0.5064
Our new approach deep CNN-LSTM	21,070.1960	12,809.5	0.6998

Fig. 5 Example of the relevant contents obtained from social media thanks to the hybrid of deep CNN-LSTM-based emergency management

proposed alert model, we applied three evaluation indices, including the mean squared error (RMSE), the mean absolute error (MAE) and goodness of fit (*R*-Square) as the loss function for model training. The expression of these evaluation indices is as follows:

$$\text{RMSE} = \frac{1}{N} * \sum_{i=1}^{N} \sqrt{(y_i - y_i^*)^2} \tag{25}$$

$$\text{MAE} = \frac{1}{N} * \sum_{i=1}^{N} |y_i - y_i^*| \tag{26}$$

$$R^2 = 1 - \frac{1}{N} * \frac{\sum_{i=1}^{N}(y_i - y_i^*)^2}{\sum_{i=1}^{N}(y_i - \ddot{y}_i)^2} \tag{27}$$

where

N represents the number of content +flow, y_i is the real content in flow i, and y_i^* is the relevant content flow. $\ddot{y}_i$ is the mean value of the relevant content number.

Data Description

We have divided the data sets into a training set and a verification set. The learning set is applied to train different deep learning models, while updating the weights and bias of the neural cell. And then the verification set checks the skill of these models.

Results

LSTM is an important part of the hybrid of Deep CNN-LSTM framework and provides vector characteristics based on historical information. The final experimental results are presented in Table 6 and Fig. 5.

In this section, we have checked the effectiveness of the proposed hybrid of deep CNN-LSTM model against the benchmarks: the RNN and LSTM prediction method are the widely used deep learning models. In the experiment, these deep learning/machine learning models must learn (finding best hyper-parameters), including find the number of neurons, the number of layers of neural networks and the activation function of the hybrid of deep CNN-LSTM model. After a complete experiment, we obtained the final configuration results of this model through the evaluation of the verification set.

To be fair, the number of relevant contents are taken as the historical information for NN, FFNN, RNN, LSTM and our new approach hybrid of deep CNN-LSTM. Further, from the RMSE and MAE, it is obviously that CNN-LSTM is more accurate than LSTM and CNN since combining the advantages of both. This result indicates that the hybrid of deep CNN-LSTM model is more suitable to retrieve relevant content than the neural network, the feedforward neural network, the original RNN and its variant LSTM model.

Conclusion and Perspectives

We have presented an ad hoc real-time managing emergency model based on a hybrid of deep CNN-LSTM for warning, situational awareness, education and damage assessment. It is built to prevent natural or anthropogenic catastrophe. It is based on a new multiview capture model from various sources. Such an approach is really useful for disaster monitoring. It also permit to inform the community about himself and/or themselves state. It also permits to get help. Content can be written informally, especially in a crisis, without any syntax, logic, noisy, containing spelling errors, abbreviations, etc.

There is only English content collected in catastrophic events using specific keywords. As a result, there may be domain-specific biases in the dataset. In parallel, content in other languages can have various types of reasons related to content in English.

The features of the emergency management model have been developed based on the analysis of specific disaster content.

This study has many potential future applications in the future work. The validation of relevant information (avoiding abusive information), the use of multiple languages (particularly French and Arabic), and the extraction of useful information to save the lives of those trapped under the rubble or the unlocking of roads at isolated corners due to a broken bridge or congested road will be the first pure improvements. The real-time paradigm would also be expanded by incorporating Big Data to look for information about past disasters that might help us validate an eventual warning that will save people in distress.

Declarations

Conflict of Interest Bejaia, July 11th, 2022 Zair Bouzidi University of Bouira—Algeria. On behalf of all the authors, the corresponding author states that there is no conflict of interest. This is done to serve and assert what is right. Zair Bouzidi.

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