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Deep Learning-Based Managing Disaster with Smart Education in Environmental Sustainability while Avoiding Fake News

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Abstract
Networking continues to increase day by day to invest increasingly our daily, creating a huge volume of various and precise data: it is not easy to collect content, especially in crisis times. We focus on Smart Education proposed as the primary tool of a hybrid of Deep Convolutional Neural Networks (CNN)-Long Short-Term Memory (LSTM)-based model to retrieve content efficiently: CNN is used to extract meaningful features from multiple sources, enabling to have qualitative and sure information, notably with an efficient fake news security, and LSTM is used to maintain long-term dependencies in the extracted features with recurrent connections. This model has been compared to previous approaches to the performance of a publicly available dataset to demonstrate its highly satisfactory performance. This new approach makes it possible to integrate artificial intelligence technologies, deep learning, social media, and detecting or avoiding fake news into the crisis management model. It is based on an extension of our previous approach, namely disaster management based on short-term memory and education: this experience constitutes a background for this model. It combines representation training with awareness and education while retrieving pattern information by combining various search results from multiple sources. We have extended it to improve our disaster management model and evaluate it in the case of COVID-19 while obtaining promising results, through past programs and experiences that have shown overwhelmingly positive effects of education for vulnerability reduction and disaster risk management, in the pursuit of Environmental Sustainability.

Keywords: Learning from Experience, Observations and Mistakes, Beginner Mode, Children education, Alert, Online Manual Rehearsal Mode, Relevant Steps, Awareness, Deep Learning, Disaster Management, Novice Mode, Smart Education, Social Media

1. Introduction

Disaster education is an operational, functional, and cost-effective risk management tool [1]. This study aimed to show the importance of education and the effect of different education methods on disaster risk reduction and the preparedness of vulnerable people.

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

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

Research on extracting content from social media can be considered a sequence learning problem [4]. Thus, we propose a new approach to managing the emergency model, based on a hybrid of deep convolutional neural network with a Long Short-Term Memory Network used thanks to its ability to learn long-term dependencies. This new approach allows the integration of artificial intelligence technologies, deep learning, and social media, in the managing crisis model [4]. This is based on an extension of our previous approach: this experience forms the background for this model [3,5]. It combines representation training with alertness, awareness, and education while integrating encapsulations from multiple 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, awareness, or education) of managers to make quick and effective decisions that could help people in need or save lives. Thus, we provide, not only, a solution to this challenge, but also, to achieve promising results.

Our study has six-fold main contributions.
1. We develop Smart Education, as a primary new unit of the model Hybrid of Deep CNN-LSTM-based Automated Learning Environment (ALE).
2. We develop the Hybrid of Deep CNN-LSTM that uses low-level capabilities of content learning of multiple sources of information (all the Web) to automatically and efficiently collect real-time reports of awareness distributed during large-scale catastrophic events, to automatically separate relevant content from non-informative information.
3. Information security is the most important concept in disaster management, notably with social networks. This is ensured here in two sequential ways, namely: First, Security by Retrieving Content from Multiple Sources that enables us to have an overview of qualitative and sure information to avoid fake news. Second, Security against Fake News.
4. 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.
5. We develop an event-independent model to filter content on various sources at a time in future events while keeping in mind the limitations of previous work and outperforming all the others.
6. Finally, we tested entirely the ALE, including Smart Education, immediately on COVID-19, from January 2020 until nowadays. Then, we conclude, by giving some perspectives.

The paper rest is structured as follows. The next section provides background on disaster education, disaster risk management in the pursuit of environmental sustainability, and related works. Section 3 introduces our new model, namely the Hybrid of Deep CNN-LSTM. We modeled it, providing details on Smart Education, with a discussion about the results obtained, notably results of original empirical studies conducted in various socio-economic, geographical, hazard, and cultural contexts providing strong and consistent evidence of the positive impact of formal education in reducing vulnerability, showing that Disaster education is an operational, functional and cost-effective risk management tool [1,6]. The basic hypothesis consists of communities that can develop the most effective long-term defense against the dangerousness of disaster and climate change by strengthening awareness and human capacity, primarily.

1.1. Background & Related Works
Online messages contain important information that can also help make quick decisions to help the affected community if they are dealt with quickly and effectively. Many types of processing techniques ranging from comparable document-aligned data, statistical analysis, from natural language processing to automated learning to computational linguistics 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 [2,3].

1.2. Disaster Education
Disasters and emergencies have been increasing all over the world [1]. Today, with technological advancement, acquiring knowledge and its application in the realm of action is regarded as the only effective way to prevent disasters or reduce their effects. The present study aimed to review the importance of education and the effect of different methods of education on disaster risk reduction and preparedness in vulnerable people. Exploring the role of higher education institutions in disaster risk management and climate change adaptation [7]. Disaster education is an operational, functional, and cost-effective risk management tool [1]. It is important to inform vulnerable people about disasters. There are different methods for educating vulnerable people, but no one is better than another. Trained people can better protect themselves and others [1].

In investigating global change affecting population vulnerability to climate variability and extremes, our purpose aims to help develop strategies enabling communities to better cope with the risk management and climate change consequences [6]. The basic hypothesis being tested consists of societies that can develop the most effective long-term defense against the dangers of disaster and climate change by strengthening awareness and human capacity, primarily through education. Education can directly influence risk perception, knowledge, and skills and indirectly improve health, reduce poverty, and promote access to resources and information. Facing climate risks or natural hazards, educated households, individuals, and societies are assumed to be more adaptive and empowered in their preparation, response, and recovery from disasters. Planning and designing comprehensive educational programs is necessary for people to cope with disasters [1].

The results of original empirical studies conducted in various socioeconomic, geographical, hazard, and cultural contexts provide strong and consistent evidence of the positive impact of formal education in reducing vulnerability. Highly educated societies and individuals are better prepared to respond to disasters while experiencing fewer negative impacts, and recovering more quickly [6].

People, notably Children who know how to react in a crisis event, community leaders who learned to warn in time, and social layers who taught to prepare themselves for hazards contributed to better mitigation strategies and information spread on dangers. Education and knowledge provided people with tools for reducing vulnerability and strategies for life-enhancing self-help. Succession disaster education consists of linking formal education in school. Along with human casualties, infrastructure damage, and material loss, health issues become a critically important problem after natural disasters. After disasters, limited knowledge about health risks and lack of awareness contribute to emerging essentially preventable infectious diseases. Survivors of natural disasters face the threat of health hazards, especially infectious diseases, due to limited sanitation supplies, services, and facilities. Integrated health education in schools and community-based disaster risk reduction plans, such as information spread, is important to create resilient communities. Water-borne and air-borne infectious diseases were the most common illnesses following major disasters. Facing disasters, schools and community centers can be agents to spread health promotion information so people become more aware of health risks in conducting good practices related to recovery, response, and notably prevention.

1.3. Risk Reduction Experience

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). Table 1 gives an overview of recent natural and anthropogenic disasters and all their damage assessment.

No	Catastrophic event	Period	Damage
1	Chlef earthquake, Algeria	Oct 10th, 1980	5,000 dead, 400,000 homeless, 20,000 homes destroyed
2	Boumerdes, Algiers	May 21st, 2003	2,266 dead, 10,261 injured, 200,000 homeless
3	Algiers flood	Nov 9-10, 2001	700 dead
4	Oued Meknassa	March 7th, 2021	7 dead, 100 missing Chlef flood
5	Wildfire 2021	Aug 09-14, 2021	More than 70 fires, 90 Algeria deaths, Several charred dwellings, livestock
6	Covid-19	May 2020-Aug 21	192,000 affected, 5,004 deaths

Table 1: Latest Unfortunate Events

Covid-19 is a pandemic of an evolution infectious disease. It first appeared in China, in November 2019 and spread 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 cancellation 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 (fake news). Luckily, with approximately 2% of the cases detected, the provisional death rate is lower than in previous coronavirus pandemics. 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 contamination number with COVID-19 continues to increase to this day. More than 4000 variants of the virus, called SARS-CoV-2- 2 according to the 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.

We suggest a new emergency management model based on a Hybrid model of Deep CNN-LSTM for warning, awareness, and education on social networks in this paper. It is based on an extension of the Recurrent Neural Network, of LSTM [5,8,9]. 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, awareness, and education while integrating encapsulations from multiple sources and retrieving information by combining multiple search results (all the Web) while being wary of fake news.

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

No	Methods, Approaches
1	Raising awareness in multicultural societies: Disaster Awareness Game (DAG) approach [10]
2	Synthesis with socio-temporal context [11]
3	Multiscale analysis of Twitter activity before, during, and after Hurricane Sandy [12]
4	Creating a Tweet Aggregation Dataset using Text Retrieval Conference (TREC) Tracks [13]

5	AI-based Semi-automated classifier for disaster response [14]
6	Summary of contextual tweets in crisis events: an extractive-abstractive approach [15]
7	Recurrent Neural Networks (RNN)-based automated learning environment to improve awareness [5]
8	LSTM-based ALE to enhance awareness and education [8,9]
9	Deep CNN-LSTM-based model to improve warning, awareness and education in a crisis event [16]
Our New Approach	Disaster Management Model Based on a Hybrid of Deep CNN-LSTM to enhance awareness

Table 2: Comparative Table using Techniques and Methods in Models with Awareness, while Including our Approach

No	Methods, Approaches
1	Summarization with social-temporal context [11]
2	Automatic disaster damage assessment through fusion of satellite, aircraft, and drone data [17]
3	Semi-automated artificial intelligence-based classifier for Disaster Response [10]
4	Summarizing situational tweets during crisis events: an extractive-abstractive approach [18]
Our New Approach	Disaster Management Model Based on a Hybrid of Deep CNN-LSTM to enhance assessment

Table 3: Comparative Table using Techniques and Methods in Models with Assessment, while Including our Approach

No	Methods	Used OSN
1	Flood Disaster Game-based Learning [19]	Twitter
2	Educational Purposes among the Faculty of Higher Education with Special Reference [20]	Twitter
3	Summarization with social-temporal context [11]	Twitter
4	Semi-automated artificial intelligence-based classifier for Disaster Response [14]	Twitter
5	Summarizing situational tweets in crisis events: An extractive-abstractive approach [15]	Twitter
6	Neural Network-based Disaster Management Model to enhance Warning [2]	Twitter & Facebook
7	Feedforward Neural Network-based Automated Learning Environment to Enhance Warning and Education from All the Web [3]	All the Web
8	LSTM-based Automated Learning Environment to enhance Warning and Education from All the Web [5, 8,9]	All the Web
9	Deep CNN-LSTM-based Managing Disaster Model to improve Warning, Awareness, and Education from the Web [16]	All the Web
Our New Approach	Disaster Management Model based on a Hybrid of Deep CNN-LSTM to improve alert, awareness, assessment, and education	All the Web

Table 4: Comparative Table using Techniques and Methods in Models with Social Networks, while Including Our Approach

Our emergency management model based on a real-time Convolutional Network-LSTM is best suited to situational awareness (see Table 2). It uses Multisource content (from all websites) (see Table 3) with training opportunities for automatically and effectively capturing the situation in real-time reports during catastrophic events on a 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).

Contents are less formal, contain words from more than one language, and have various grammatical and spelling errors, while being, for the most part, unstructured, fuzzy, and short-lived [2,3]. Their length and content vary considerably [21]. We detected emotions using features, such as interjections, blasphemy, emoticons, and the general feeling of the message. These are widely used to convey emotions such as danger, surprise, happiness, etc.

No	Methods
1	Summarize situational tweets in crisis events: An extractive abstractive Approach [15]
2	Educational Purpose of the Faculty of Higher Education with Special Reference [22]
3	Game-based Learning of Flood Disasters [1]
4	The importance of education on disasters and emergencies [20]
5	Challenges and opportunities of education programs [19]
6	A tabletop simulation system for disaster education [23]
7	Flood protection computer game for disaster education [24]
8	Using immersive game-based virtual reality to teach fire safety skills to children [25]
9	Penumbral Tourism: Place-based Disaster Education via real-world Disaster Simulation [26]
10	A mixed reality game to investigate coordination in disaster Response [27]
11	Feed Forward Neural Network-based Automated Learning Environment with Smart Education [3]
12	LSTM-based Automated Learning Environment with Smart Education [8]
13	Deep CNN-LSTM-based Managing Disaster Model with Smart Education [16]
Our New Approach	Disaster Management Model Based on a Hybrid of Deep CNNLSTM to Enhance Education

Table 5: Comparative table using techniques and methods in models with education, while including our approach

No	Methods
1	Deep Learning, Big Data, and High-Performance Computing to enhance Business and Marketing, while warning of Fake News [5]
Our New Approach	Disaster Management Model based on a Hybrid of Deep CNNLSTM to enhance Detecting and Fighting Fake News

Table 6: Comparative table using techniques and methods in models with Detecting and Fighting Fake New

The content was captured from online channels followed by the online tool Radian6 [21]. Actually, many networking platforms enable access to their content by Application Programming Interface (API) [21]. 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.

1.4. Related Works

IT-based crisis management provides decision-making support while raising public awareness of disasters, supports the communication and dissemination of information and alerts, and promotes the implementation of crisis management-related regulations [28]. While the Disaster management model is based on Geospatial Information Technology (GIS), however, it is limited to certain (natural) disasters [27]. It is also available for effective use of satellite positioning, remote sensing, and GIS, for disaster monitoring and management. Dealing only with natural disasters, Internet GIS for Crisis Management as well as Disaster management models based on geospatial information technology, remote sensing, and global satellite navigation, creates new organization and networking arrangements, thus revealing the power of cross-networking.

The neural network-based disaster alert models are one of the first to use multiple sources, namely Twitter and Facebook, for capturing messages during a crisis [2]. Followed by the smart interface-based automated learning environment to improve disaster warning, while introducing smart education [3]. While consists of an RNN-based Automated Learning Environment to improve awareness [5]. Based on LSTM, it is to improve the lack of RNN of the previous model [5,8,9]. It is introduced to improve also education. Finally, we have the hybrid of CNN and LSTM, used to successfully improve disaster warning, awareness and education.

1.5. New Model of Emergency Management

We present our new network model, Deep CNN-LSTM. The LSTM layer is shown to be powerful in handling temporal correlation. Its extension has convolutional structures in both input-state and state-to-state transitions, which will solve this problem. By stacking multiple Deep 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 previous sequence of observed social networking to prevent an event in a local region, such as Algiers, London, or Paris. From an 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 periodic 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):

$$\hat{Y}_{t+1}, \cdots, \hat{Y}_{t+K} =$$

$$\arg \max_{\mathbf{X}_{t+1},\ldots,\mathbf{X}_{t+K}} p(\mathbf{X}_{t+1}, ..., \mathbf{X}_{t+K} \mid \mathbf{Y}_{t-J+1}, ..., \mathbf{Y}_{t-J+K}) \quad (1)$$

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 Figure), 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:

$$e = (w_1, ..., w_i, ..., w_n) \quad (2)$$

containing words w_i € 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 follows:

$$-ln(p(x)) \quad (3)$$

Symmetrically, p(x) must be as small, if y = 0. The error is then:

$$-ln(1 - p(x)) \quad (4)$$

So, the general formula is:

$$error = -y * ln(p(x)) - (1 - y) * ln(1 - p(x)) \quad (5)$$

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 are regularized variants of multilayer perceptron's (each neuron is linked to the next layer) [29]. The *fully-connectedness* makes them susceptible to overfitting information (See Figure 1).

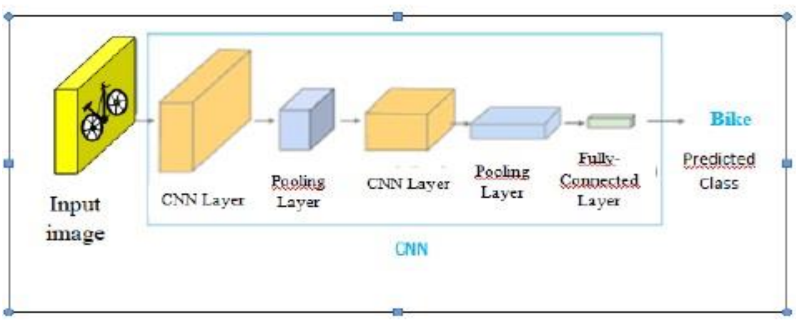

Figure 1: Convolutional Neural Network Structure (CNN)

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

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

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

CNNs use very little pre-processing: they learn the filters, hand-engineered in conventional algorithms.

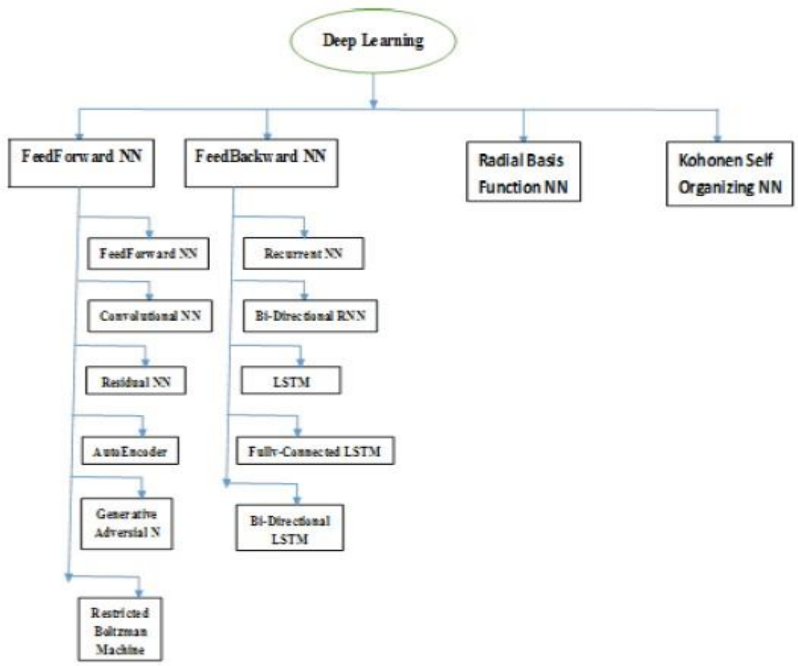

Figure 2: Classification Deep Learning Models

A Feed Forward Neural Network (FFNN) is a binary classifier. It is organized in layers, as human neuron. Each node relates to all others in these layers: Layers connections can have various weight measuring the potential amount of the network knowledge. Information processing requires data entry from the input units, flowing through the network, from one layer to the other before the output units. Normally (classifier), there will be no feedback between layers. FFNN handles tasks based on first come first serve input bases. As for the Feed-Backward NN (FBNN), it uses internal state memory to process sequence of data inputs, as Recurrent Neural Network (RNN). Figure 1 shows a new classification of deep learning models.

1.6. Convolutional Neural Network (CNN)

As regularized variants of multilayer perceptron's, CNNs are totally linked networks, where each neuron in one layer is linked to the next layer [4,30]. The fully-connectedness network makes them susceptible to over-fitting information: traditional methods of regularization include adding, to the loss function, magnitude measurement of weights. Taking a different approach to regularization, con-evolutionary networks (CNNs), are inspired by biological processes, where the pattern of communication between neurons follows the organization of the visual cortex of the animal: individual cortical neurons respond to stimuli only in a small area of the visual (receptive) field. CNNs use very little pre-processing: they learn the filters that were hand-engineered in conventional algorithms [4].

The current state formula is:

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

Applying activation function tanh:

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

σ is weight, h is the single hidden vector, σ_{hh} is the weight at previous hidden state, σ_{xh} is the weight at current input state, tanh is the Activation function implementing a Non-linearity that squashes the activations to the range [−1, 1].

1.7. Long Short-Term Memory (LSTM)

Long Short-Term Memory, efficient RNN architecture for sequence learning, introduces the memory cell, a computation unit that replaces artificial neurons in the hidden layer [4]. A memory cell is a component of LSTM units that can hold information in memory for a long time. The vanishing gradient problem of RNN is thus resolved here. LSTMs are suitable for classification, processing, and forecasting of time series given a delay of unknown duration. Thanks to the back propagation, it trains the model. LSTM network has three gates (see Figure): The computation mathematical definition of LSTM model can be described as follows:

$$i_t = \sigma(\omega_{ix} * x_t + \omega_{ih} * h_{t-1} + b_i) \quad (9)$$

$$c_t = f_t * c_{t-1} + i_t * \tanh(\omega_{cx} * x_t + \omega_{ch} * h_{t-1} + b_c) \quad (10)$$

$$f_t = \sigma(\omega_{fx} * x_t + \omega_{fh} * h_{t-1} + b_f) \quad (11)$$

$$j_t = \sigma(\omega_{jx} * x_t + \omega_{jh} * h_{t-1} + b_j) \quad (12)$$

$$h_t = j_t * \tanh(c_t) \quad (13)$$

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

The formula for the current state is

$$h_t = f(h_{t-1}, x_t) \quad (14)$$

Applying activation function tanh:

$$h_t = \tanh(\sigma_{hh} * h_{t-1} + \sigma_{x_h} * x_t) \quad (15)$$

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:

$$y_t = \sigma_{hy} * h_t \quad (16)$$

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:

$$h_t = \alpha(\sigma_{hx} * x_t + \sigma_{hh}.h_{t-1} + b_h) \quad (17)$$

$$y_t = \beta(\sigma_{yh} * h_t + b_y) \quad (18)$$

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. In training the model using back-propagation, LSTM is well-suited to classify, process and forecast time series, thanks to time lags of unknown length. 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 (see Figure 3):

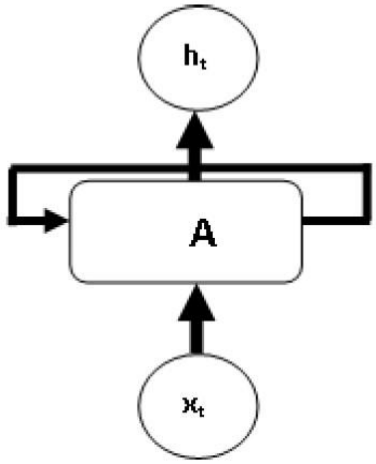

Figure 3: Overview of LSTM, its Gates and Activation Functions

$$i_t = \sigma(\omega_{ix} * x_t + \omega_{ih} * h_{t-1} + b_i) \tag{19}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(\omega_{cx} * x_t + \omega_{ch} * h_{t-1} + b_c) \tag{20}$$

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.

$$f_t = \sigma(\omega_{fx} * x_t + \omega_{fh} * h_{t-1} + b_f) \tag{21}$$

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.

$$j_t = \sigma(\omega_{jx} * x_t + \omega_{jh} * h_{t-1} + b_j) \tag{22}$$

$$h_t = j_t \odot \tanh(c_t) \tag{23}$$

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 [31]:

$$\phi(x) = \frac{1}{1 + e^{-x}} \tag{24}$$

and tanh :

$$\tanh(x) = \frac{1 - e^{-2x}}{1 + e^{-2x}} \tag{25}$$

1.8. Proposed of Hybrid of Deep CNN-LSTM-Based Model

The whole Deep CNN-LSTM modeling procedure has been introduced with systematic methods, while trying to obtain consistently efficient models, such as training data collection, data pre-processing and post-processing, weight initialization, learning of algorithms, error functions and different types of activation functions: our leitmotiv is to find the best architecture, although performance is affected by many factors.

We have a Deep CNN-LSTM with hidden layers taking as contents of input:

$$\epsilon = (\omega_1, ..., \omega_i, ..., \omega_n) \qquad (26)$$

containing words W, from a finite vocabulary V, i.e. the contents set issued from social media giving as output the relevant content e_k. Let:

$$\forall i \in [1, N] \quad e_i \in C_n = \mathbf{E} \quad \& \quad e_i = (w_{i1}, w_{i2}, ..., w_{in}) \qquad (27)$$

containing words from the set of words W where each one comes from a finite vocabulary V. The content incorporation of the source message i relevant for, at least, a keyword or a hashtag such as:

Transforming e_i into e_k can be described, with the automated learning, by:

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

$$\max_{k \in [1,K]} \left\{ e_i \longrightarrow e_k = \{ e_i \quad / \quad e_i \quad Relevant \quad for \quad (h_j \ , \ w_l) \} \right\} \qquad (28)$$

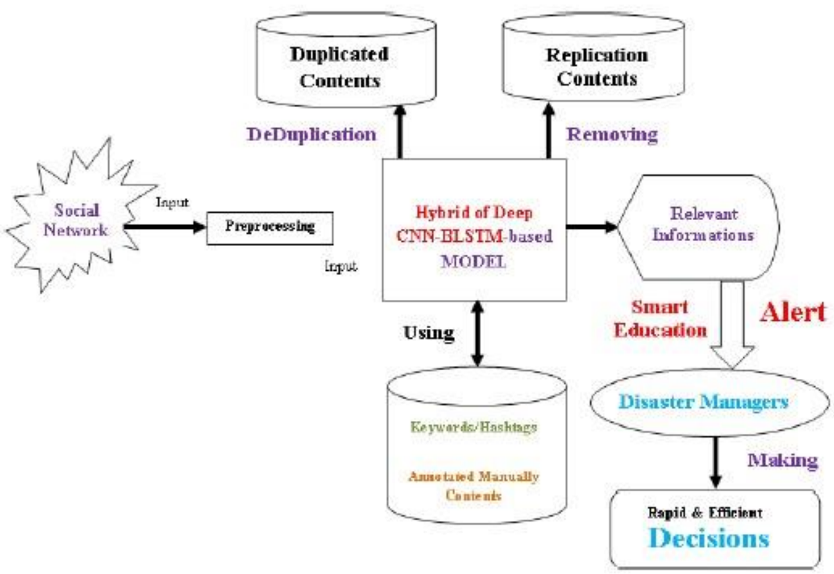

Figure 4: Functioning of Deep CNN-LSTM Model

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

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 EK set. Figure 3 shows the functioning of the Hybrid of Deep CNN-LSTM-based Emergency Management.

1.9. Smart Education

Education plays a leading role in awareness, disaster reduction and, generally, human security as part of sustainable development. Previous experiences have shown the positive effects of education in disaster risk management, especially children education. It has turned out that those who have been made aware of the phenomenon of disasters and how to respond to such situations are still able to react quickly and appropriately, while warning others and protecting themselves in an emergency [22].

This model is designed to support an introductory traineeship in disaster management for citizens, trainees and future disaster managers [3]. So, the trainee can use this tool in three modes. Novice Mode enables him to use a complete set of automated design and learning tools, such as observing different programs at work, experimenting them and gradually learning from his experience, observations and mistakes [3].

Beginner Mode enables him, at any point, to ask it for generating (move on) the next step. Analyzing knowledge, the tool provides both the optimal stage and a list of all relevant operations. Not satisfied with proposed operation, the trainee can choose any appropriate operation using adaptive hierarchical menus.

In the Online manual rehearsal Mode, at any time during the training, the trainee has a menu to access all previous courses, such as:

• Presentation of any previously learned concept,

• Demonstration of all the examples learned and analysis of any problem already explained or resolved.

This mode provides access to the material learned from the course as a reference [3,5,8,16,9, 30]. Thereby supporting example-based online help.

Educational messages play a role in raising awareness in times of public health crisis [16,30]. This pandemic is becoming an infectious disease caused by the corona virus SARS-CoV-2. Education about the Covid-19 consists of

- advising to always reinforce preventive hygiene, namely
- the elimination of physical contact, kisses and handshakes,
- coughing and/or sneezing into the crook of the elbow,
- using disposable tissues
- respect physical/social distancing,
- wear a bib,
- stop gatherings, trips and any major event,
- promote hand washing and
- avoid any social or cultural gatherings.

Disaster education consists of constantly rehashing these tips on all information channels, websites and all social and networking media to have maximum awareness [3,5,8,9,16,30]. Health education and promotion can be integrated into curriculum-based or training-based programs as drills, modules, and visual media.

This emergency model is also designed to support an introductory course to prepare the health system and the health workforce to respond to the health needs of affected populations: it consists of standardizing good practice by developing the basic skills of essential knowledge and skills for health workers in disasters [16,30]:

- skills appropriate to a given position or function during a disaster;
- unique competencies that focus on skill level rather than role or function;
- skills based on specific roles as well as skill levels;
- graduated skills in emergency nursing according to the stages of the disaster management process;
- skills specified as a basis for different target groups, and
- transversal skills applicable to all health personnel.

Unfortunately, imprecise and inconsistent terminology is evident among the skill sets reviewed. There is a need for universal acceptance and application of these skills [3]. The purpose of this approach is to develop a framework and standardized terminology for articulating competency sets for disaster health professionals that are universally accepted and appropriate [16,30].

Education plays a leading role in disaster reduction and human security in the pursuit of sustainable development. Previous experiences have shown the positive effects of education in disaster risk management, especially children education. It has turned out that those who have been made aware of the phenomenon of disasters and how to respond to such situations are still able to react quickly and appropriately, thereby warning others and protecting themselves in an emergency.

1.10. Information Security

Information security is due to the confidentiality, integrity, availability, non-repudiation (concerning a transaction between several correspondents) and authentication of information. Unfortunately, none of these characteristics of information security can be assured with social media. Information security is the most important concept in disaster management, even with social networks. This is ensured here in two sequential ways, namely: First, Security by Retrieving Content from Multiple Sources and finally, Security against Fake News [2-5,8,9,16,30].

1.10.1. Security by Retrieving Content from Multiple Sources

The use of several sources of information guarantees the quality of the information and in particular its safety. False information is quickly spotted among so much information and quantities of information. As soon as doubt arises, with information presented in different ways and differently, precautions will be taken quickly to verify this information even more differently to validate or not the latter [2-5,8,9,16,30].

1.10.2. Security Against Fake News

There is also cyber-security against any new threat generating additional risks with levels of importance. These potential attacks can make us very vulnerable. They are of different kinds, namely: social engineering (phishing, ...), network eavesdropping (WireShark), malicious code, Trojan horse, spyware (keyloggers), bots and human bots, ... [5,16,30]. Data breaches remain relentless and the size of leaked data sets is steadily increasing. The secure computing concept promises to keep data encrypted, protected at all times and unavailable always to breaching attackers.

The concept of fake news is defined as misleading content including conspiracy theories, rumors, clickbaits, fabricated data (data breaches), and satire [5]. The spread of fake news has become a global issue that needs to be attended immediately [16]. Fake news is defined by as misleading content including conspiracy theories, rumors, clickbaits, fabricated news, and satire. It is defined as misinformation and disinformation both, including false and forged information, that is spread on purpose to mislead people or to fulfill a propaganda. It is considered as a vehicle of purposely targeted fabricated news spread to affect the cognitive activities of a user through user-content interaction by indirectly affecting his unconscious behavior. This unconscious behavior, can further strengthen confirmation bias among users and aid in further spread of fake news, notably humans have always been attracted to sensationalism and controversies [16]. It is the case of the recent spread of false information about COVID 19 vaccines (and dangerous scientific treatment methods), political smear campaigns during elections [5].

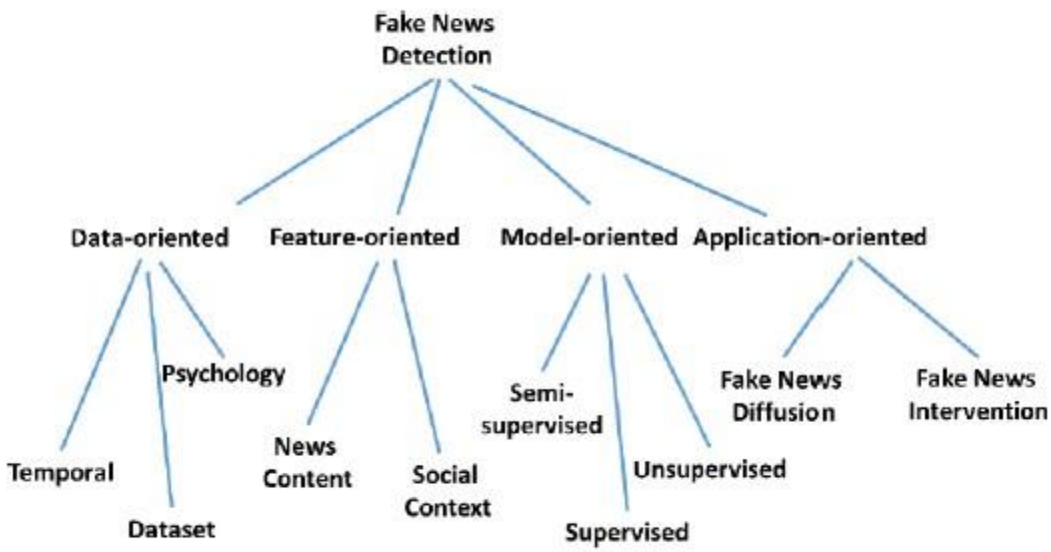

Figure 5: Taxonomy of Detecting Online Fake News

In order to clearly understand the spread of fake news, it is important examining components that can be divided into four main categories namely creator/spreader, target victims, content and social context [30].

- Creators/Spreaders: Creators generate fake news and broadcasters spread it by sharing it. They can be human or non-human (social robots & cyborgs). Social bots, algorithms autonomous, can create content and increase its reach. Cyborgs are a hybrid between human accounts and social bots [30].
- Target Victims: that are the group of people or organizations, namely online customers (exposed to scams) or patients (exposed to false medical information), and so on.
- News Content: comprises of physical contents (headings and visual features to attract users), namely Clickbait and hashtags catching viewers' attention and non-physical contents (opinions and sentiments) creating polarity and change of views.
- Social Context: referring to the social environment.

Fake News Spreads are categorized based on three categories, namely source, propagation and target-based features.

1.11. Source-Based Account Detection

A source of fake news can be a human, bot or cyborg. Features of their source are classified into three main categories, namely: feature of personality, historical and of credibility.

1.12. Propagation-Based Accounts Detection

A propagator, disseminating fake news widely to increase its reach to maximum victims, has features classified into three main categories, namely user engagement, time dynamics and platform-based features [30].

1.13. Target-Based Accounts Detection

The target features identify end users that are affected by the fake news. A target can be a human, bot or cyborg depending on the nature and domain of fake news. Although fake news can reach almost all the users through social media, an easy target will be those people that are more vulnerable and prone to get influenced by the fake news [5].

Victim dynamics mean thoroughly understanding the details of the end user. The details can include age, gender, education history, account creation history, network of followers, location etc. Generally new users with limited exposure to social media are targets of fake news spreaders, as they tend to believe anything presented to them due to lack of exposure, as well as Teenagers and aged people with limited knowledge of possibilities of fake news on social media are an easy target. Similarly, people with low qualifications and coming from rural areas are more prone to be the victims of fake news [16].

2. Discussion about Results

Exploring the role of higher education institutions in disaster risk management and climate change adaptation. In investigating global change affecting population vulnerability to climate variability and extremes, our purpose aims to help develop strategies enabling communities to better cope with the climate change consequences [7].

The goal is to maximize the size K of the set EK. To demonstrate the validity of our model, we examined specific events the Bejaia seism in March 18st, 2021, the Oued Meknassa Flood in Chlef in March 7st, 2021, Wildfire in Algeria in August 2021 and Covid-19 Coronavirus Pandemic - and post-event messages on two social media: Twitter and Facebook. The Twitter Search API was used to collect tweets, and the Facebook Search API was used to collect Facebook messages.

We use the search keywords ’Bejaia’, ’Seism’ and ’earthquake’, ’Chlef’ and ’flood’, ’Wilfire 2021’, ’Algeria’, ’Covid-19’ and ’Coronavirus 2019’ for, respectively the earthquake in Bejaia, the floods in Chlef, wilfire in Algeria and Covid-19 Coronavirus Pandemic. After processing inconsistent content such as punctuation, special characters, de-duplication, replication content and even false information thanks to Deep CNN-LSTM, all experiments reported here are executed for all datasets [2]. We identified a set of disaster-specific information needs. It is a set of hashtags and keywords from multiple sources (Twitter and Facebook). There were different types of contents posted by users to get information about an unfavorable and dire situation at a certain time. The core of social media crisis management is data collection and filtering. The algorithms used to warn and alert are based on the accuracy of the contents of social networking sites. Any effort should be made to increase the number of crisis-relevant contents while eliminating non-informative content and false news.

Models	Bejaia Seism
Support Vector Machine (SVM) [30]	475
Neural Network [2]	531
Feed-forward Neural Network [3]	852
Recurrent Neural Network [5]	875
LSTM [8,9]	908
Hybrid of Deep CNN-LSTM [16]	928
Our New Approach	991

Table 7: Examples of Relevant Content of the Seism of Bejaia on March 18th, 2021 for a Set of Hashtags and Keywords from multiple sources

Models	Oued Meknassa Flood in Chlef
Support Vector Machine (SVM) [30]	463
Neural Network [2]	501
Feed-forward Neural Network [3]	525
Recurrent Neural Network [5]	601
LSTM [8,9]	657
Hybrid of Deep CNN-LSTM [16]	682
Our New Approach	695

Table 8: Examples of Relevant Contents of Floods of Oued Meknassa in Chlef for a Set of Hashtags and Keywords from multiple sources

Models	Wildfire in Algeria
Support Vector Machine (SVM) [30]	1435
Neural Network [2]	1531
Feed-forward Neural Network [3]	2549

Recurrent Neural Network [5]	2734
LSTM [8,9]	2804
Hybrid of Deep CNN-LSTM [16]	2911
Our New Approach	2943

Table 9: Examples of Relevant Content Wildfire in Algeria for August 16th 19th, 2021 for a Set of Hashtags and Keywords for all social networks

Examples of Relevant Content of Wildfire in Algeria of August 16th-19th, 2021 for a Set of Hashtags and Keywords from multiple sources.

Models	Covid-19 in Algeria
Support Vector Machine (SVM) [30]	2364
Neural Network [2]	2495
Feed-forward Neural Network [3]	2634
Recurrent Neural Network [5]	2772
LSTM [8,9]	2814
Hybrid of Deep CNN-LSTM [16]	2971
Our New Approach	2998

Table 10: Examples of Relevant Content of Covid-19 in Algeria from March 2020 to date, for a Set of Hashtags and Keywords from multiple sources

The contents are represented by a sequence of transactions T = (t_1, ..., t_n) and each message contains keywords or hashtags. These messages are manually annotated to remove not related (non-informative) to the disaster. Table 9 and Figure 4 show the comparison between the results obtained in this approach with our previous results for Algiers Floods. Table 10 and figure compare the results obtained in this approach with our previous results for Oued Meknassa Flood in Chlef.

Examples of Relevant Content Covid-19 in Algeria, from March 2020 to date, for a Set of Hashtags and Keywords for all social networks. Table 11 and Figure 6 show the comparison between the results obtained in this approach with our previous results, namely Neural Network, Feed-forward Neural Network, RNN, LSTM and CNN-LSTM as this work, for Covid-19 in Algeria [2,3,5,8,9,16].

2.1. Manipulating of the Emergency Management Model

The disaster manager, once registered, with his own username and password, thus defines his own environment. He can thus launch the Emergency Management Model3, already configured, to extract content from social media and analyze it.

Models	Bejaia Seism	Meknassa Flood in Chlef	Wildfire in Algeria	Covid-19 in Algeria
Support Vector Machine (SVM) [30]	475	463	1435	2364
Neural Network [2]	531	501	1531	2495
Feed-forward Neural Network [3]	852	525	2549	2634
Recurrent Neural Network [5]	875	601	2734	2772
LSTM [8,9]	908	657	2804	2814
Hybrid of Deep CNN-LSTM [16]	928	682	2911	2971
Our New Approach	991	695	2943	2998

Table 11: Overview of Comparison between the Results obtained in this Approach

The keywords/hashtags and manually annotated contents are already operational: we can view with the Viewing menu. Listening and Tracking is programmed to the entire Web. Processing is set to Streaming or Smart Data, the alert to Automatic and Learning to Feed-forward Neural Learning, Recurrent NN, LSTM, Bidirectional LSTM, CNN or Deep CNN-LSTM. This manager can simply follow the progress of this treatment by viewing relevant content, duplicated content and replication content using the Viewing menu. Even the alert is made automatically. In the event that he wishes to participate (intervene) in the process, he can for example modify the type of learning with the Learning menu, change listening and monitoring, processing or alert. This Emergency Management Model leads, at any time, to visualize, with Viewing, the various available keywords, manually annotated, relevant and duplicate or replication contents. It enables Streaming or just providing a message (especially for new users) in Content Treatment. In case of Streaming, we have to specify, in Listening / Monitoring, Twitter (Twitter is chosen optionally), other Social Networks or the entire Web.

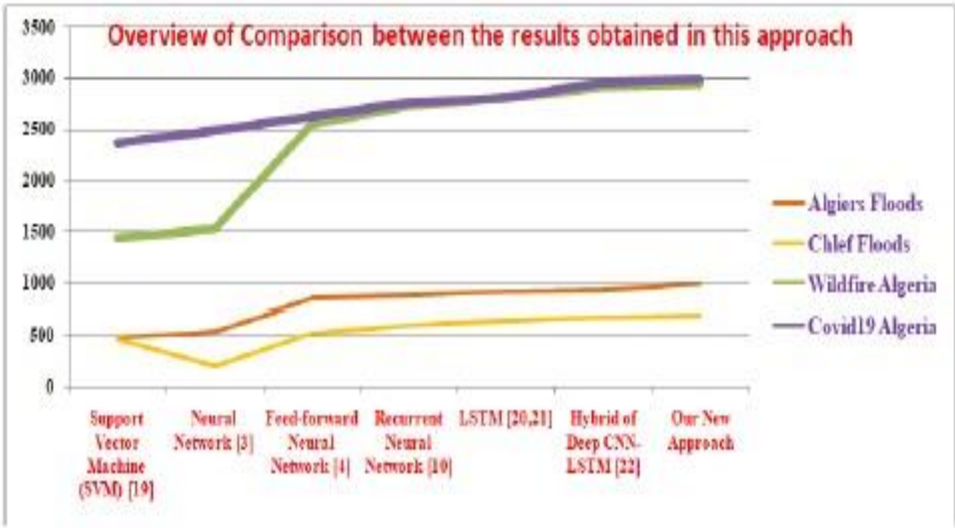

Figure 6: Overview of Comparison between the Results Obtained in this Approach

Models	RMSE	MAE	R^2
Support Vector Machine (SVM) [30]	15,286,2154	16,523	0,2937
Neural Network [2]	17088.3797	18,471	0.3284
Feed-forward Neural Network [3]	16100.9272	19,461.5	0.4645
Recurrent Neural Network [5]	13359.4722	19,962.5	0.4805
LSTM [8,9]	16704.4894	19,557	0.5064
Hybrid of Deep CNN-LSTM [30]	21070.1960	12,809.5	0.6998
Our New Approach	58.7149	13789.75	0,9793

Table 12: Overview of Comparison between the Results Obtained in this Approach

The Neural Networks and currently Deep Learning are used in various applications with great success. The biggest advantage is that they do not require a problem-solving algorithm, but they learn from examples, much like humans do. Their second benefit is an inherent generalization power. This implies that patterns similar to are identified and answered to.

2.2. 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 pre- processed. 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. Tables 6, 8, 9, 10 and 11 and Figure 6 are an example of assessment of corona virus Covid-19.

2.3. Evaluation Criteria

An excellent alert template is needed to collect messages from a possible dis- aster. To verify the performance of the 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:

$$RMSE = \frac{1}{N} * \sum_{i=1}^{N} \sqrt{(y_i - y_i^*)^2} \quad (29)$$

$$MAE = \frac{1}{N} * \sum_{i=1}^{N} |y_i - y_i^*| \quad (30)$$

$$R^2 = 1 - \frac{1}{N} * \frac{\sum_{i=1}^{N}(y_i - y_i^*)^2}{\sum_{i=1}^{N}(y_i - \ddot{y}_i)^2)} \quad (31)$$

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

2.4. 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.

3. Results

LSTM is an important part of the CNN-LSTM framework and provides vector characteristics based on historical information. The final experimental results are presented in respectively Table 6 and Figure, Table 8, Table 9, Table 10 and finally Table 11 and Figure 6.

In this section, we have checked the effectiveness of the proposed 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 neural network. After a complete experiment, we obtained the final configuration results of this model through the evaluation of the verification set.

Models	RMSE	MAE	*R2*
(Neural Network) [2]	17 088.3797	18 471	0.3284
(FeedForward NN) [3]	16 100.9272	19 461.5	0.4645
(Recurrent NN) [5]	13 359.4722	19 962.5	0.4805
(LSTM) [8,9]	16 704.4894	19 557	0.5064
Our New Approach	21 070.1960	12 809.5	0.6998

Table 13: Examples of Relevant Content of Covid-19 for a Hashtags and Keywords Set from social media

To be fair, the number of relevant contents is taken as the historical information for NN, FFNN, RNN, LSTM and our new approach 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 proposed model is more suitable to retrieve relevant content than the Neural network, the Feedforward Neural Network, the original RNN and its variant LSTM model

4. Conclusion and Perspectives

In this paper, we covered everything related to Disaster Risk Management in the pursuit of Environmental sustainability using Smart Education. Exploring the role of higher education institutions in disaster risk management and climate change adaptation, in investigating global change affecting population vulnerability to climate variability and extremes, our purpose aims to help develop strategies enabling communities to better cope with the disaster risk and climate change consequences, in the environmental sustainability.

We have presented an ad hoc real-time managing emergency model based on a Hybrid of Deep CNN-LSTM for warning, awareness and education. It is built to prevent natural or anthropogenic catastrophe. It based on a new Multiview capture model from multiple sources. Such an approach is really useful for disaster monitoring. It also permits to inform the community about itself and/or themselves state. It permits also to get help. Content can be written informally, especially in a crisis, without any syntax, neither logical, 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 Emergency Management uses social media in Algeria, such as different models of disaster management, the Emergency Management Model based on Deep Convolutional NN-Bidirectional LSTM (Deep ConvBLSTM). This one is nothing more than an extension of our real-time previous alert models used for managing natural or anthropogenic disasters [2,3,5,8,9,16]. This is just the beginning of this emergency management model. Thus, among the perspectives, we will make available to users, mainly claim managers, a fairly rich and comprehensive emergency model. We intend to integrate all the other phases of disaster management, namely mitigation and preparedness (before a disaster) and recovery (after a disaster). We also plan to implement all techniques hybrids of Deep Learning, to enhance automated learning.

This study has many potential future applications in 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. We intend to develop an automated learning environment that will train volunteers in content concept, content satisfaction, duplicate content, alert, and finally all concepts of disaster management, using as a core unit the Enhanced Smart Education that will be integrated as Online Game of Smart Disaster.

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Ethical Statement

Bejaia, January 02nd, 2024 Zair Bouzidi University of Bejaia – Algeria. On behalf of Z. Bouzidi, 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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