Disaster Management with Intelligent Education Utilizing Deep Learning and Social Media to Achieve Environmental Sustainability While Countering False News

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Abstract

It is not simple to gather material, particularly during times of crisis, since networking keeps growing and investing more and more of our everyday lives, producing a tremendous amount of diverse and accurate data. With a hybrid model based on Deep Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), we aim to effectively retrieve material via Smart Education: Combining convolutional neural networks (CNNs) with long short-term memories (LSTMs) allows for the extraction of relevant characteristics from a variety of sources, resulting in qualitative and reliable information—especially when it comes to effectively securing against false news. To prove its excellent performance, this model was tested on a publically accessible dataset and compared to other methods. The crisis management model may now include artificial intelligence, deep learning, social media, and the detection or avoidance of false news thanks to this new methodology.

The foundation of this model is an expansion of our earlier method, which was catastrophe management centred on education and short-term memory. Retrieving pattern information by merging different search results from diverse sources, it blends representation training with awareness and education. In the pursuit of environmental sustainability, we have expanded it to enhance our disaster management model and test it with the COVID-19 case study. This is all in an effort to build on previous programs and experiences that have demonstrated the tremendously beneficial effects of education on reducing vulnerability and managing disaster risk.

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

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 event, to timely share information has become 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 significate differences in the information obtained [2, 3]. To get a complete event view, it is important to collect contents from various sources. 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 [4, 5].

Several automated systems have been designed to help managers identify and filter useful information posted on the Web. Most of the work has focused on using only 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. The design of managing emergency systems using multiple information sources (the entire Web), and dedicated entirely to warning, awareness and education is a challenge.

Research on extracting content from social media can be considered as sequence learning problem [11]. 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 and social media, in the managing crisis model [11]. This is based on an extension of our previous approach this experience forms the background for this model. It combines representation training with alert, 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 [3, 12].

In this article, we try to identify relevant content related to the upcoming disaster event. Once these information are retrieved and cleaned of no 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 to 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.

• We develop Smart Education, as a primary new unit of the model Hybrid of Deep CNN-LSTM-based Automated Learning Environment (ALE).
• 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.
• Information security is the most important concept in disaster management, notably with social networks. Retrieving Content from Multiple Sources that enables us to have an overview of qualitative and sure information to avoid fake news ensures this here in two sequential ways, namely: First, Security. Second, Security against Fake News.
• 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.
• 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.
• Finally, we tested entirely the ALE, including Smart Education, immediately on the Covid-19, since January 2020 until nowadays. Then, we conclude, in 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 the environmental sustainability and related works. Section 3 introduces our new model, namely the Hybrid of Deep CNN-LSTM. We modelled 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 can develop the most effective long-term defense against the dangerousness of disaster and climate change by strengthening awareness and human capacity, primarily through education. Then, we conclude, giving some perspectives.

Background & Related works

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

Disaster Education

Disasters and emergencies have been increasing all over the world [1].

Todays, with technological advancement, acquiring knowledge and its application in the realm of action is regarded as the only effective way for prevent disasters or reducing its 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 is. 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 can develop the most effective long-term defence 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 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 for responding to disasters, while experiencing fewer negative impacts, and recovering more quickly [6].

People, notably Children who know reacting in crisis event, community leaders who learned to warn in time, and social layers who taught preparing themselves for hazards contributed to better mitigation strategies and information spread on dangers [8]. Education and knowledge provided people with tools for reducing vulnerability and strategies of life-enhancing self-help. Succession disaster education consists of linking formal education in school [9].

Along with human casualties, infrastructure damage and material loss, health issues become a critically important problem after natural disasters [10]. 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 the disasters, schools and community centres can be agents to spread health promotion information for people to become more aware of health risks in conducting good practices related to recovery, response, and notably prevention.

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.

Covid-19 is a pandemic of an evolution 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 cancellation of many sporting and cultural events around the world, the adoption of containment measures by several countries to postpone the creation of new centres 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 corona virus 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 contaminations number with the Covid-19 continues to increase to this day. More than 4000 variants of the virus, called SARS-CoV2 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.

Table 1: Latest Unfortunate Events

No Catastrophic event	Period	Damage
Chlef earth1 quake, 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 Wilfire 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

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 [12]. It is based on an extension of Recurrent Neural Network of LSTM [13, 39]. 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).

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 automatic and effectively capturing the situation in real time 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).

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 [2, 3]. Their length and content vary considerably [37]. 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.

The content was captured from online channels followed by the online tool Radian6 [37]. Actually, many networking platforms enable access to their content by Application Programming Interface (API) [37]. Online listening tools.

Table 2: Comparative Table Using Techniques and Methods in Models with Awareness, While Including Our Approach

Approaches	Methods
[21]	Raising awareness in multicultural societies: Disaster Awareness Game (DAG) approach
[19]	Synthesis with socio-temporal context
[20]	Multiscale analysis of Twitter activity before, during, and after Hurricane Sandy
[22]	Creating a Tweet Aggregation Dataset using Text REtrieval Conference (TREC) Tracks
[36]	AI-based Semi-automated classifier for disaster response
[23]	Summary of contextual tweets in crisis events: an extractive-abstractive approach
[12]	Recurrent Neural Networks (RNN)-based automated learning environment to improve awareness
[13, 39]	LSTM-based ALE to enhance awareness and education
[14]	Deep CNN-LSTM-based model to improve warning, awareness and education in crisis event
Our New Approach	Disaster Management Model based on a Hybrid of Deep CNN-LSTM to enhance awareness

Table 3: Comparative Table Using Techniques and Methods in Models with Assessment, While Including Our Approach

Approaches	Methods
[19]	Summarization with social-temporal context
[24]	Automatic disaster damage assessment through fusion of satellite, aircraft and drone data
[21]	Semi-automated artificial intelligence-based classifier for Disaster Response
[38]	Summarizing situational tweets during crisis events: an extractive-abstractive approach
Our New Approach	Disaster Management Model based on a Hybrid of Deep CNN-LSTM to enhance assessment

Serve as a model for collecting content, cleaning it up from non-informative information, enabling relevance through the learning corpus using tagged messages, and analysing results for alert, situational awareness and disaster education.

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 promote the implementation of crisis management-related regulations. While Disaster management model is based on Geospatial Information Technology (GIS), however, it is limited to certain (natural) disasters [31, 33]. 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

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

Ref	Methods	Used OSN
[25]	Flood Disaster Game-based Learning	Twitter
[26]	Educational Purposes among the Faculty of Higher Education with Special Reference	Twitter
[19]	Summarization with social-temporal context	Twitter
[36]	Semi-automated artificial intelligence-based classifier for Disaster Response	Twitter
[23]	Summarizing situational tweets in crisis events: An extractive-abstractive approach	Twitter
[2]	Neural Network-based Disaster Management Model to enhance Warning	Twitter & Facebook
[3]	FeedForward Neural Network-based Automated Learning Environment to enhance Warning and Education from All the Web	All the Web
[12, 13, 39]	LSTM-based Automated Learning Environment to enhance Warning and Education from All the Web	All the Web
[14]	Deep CNN-LSTM-based Managing Disaster Model to improve Warning, Awareness and Education from All the Web	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 5 Comparative table using techniques and methods in models with education, while including our approach

Approaches	Methods
[23]	Summarize situational tweets in crisis events: An extractive abstractive approach
[35]	Educational Purpose of the Faculty of Higher Education with Special Reference
[1]	Game-based Learning of Flood Disasters
[26]	The importance of education on disasters and emergencies
[25]	Challenges and opportunities of education programs
[27]	A tabletop simulation system for disaster education
[28]	Flood protection computer game for disaster education
[29]	Using immersive game-based virtual reality to teach fire-safety skills to children
[30]	Penumbral Tourism: Place-based Disaster Education via Realworld Disaster Simulation
[31]	A mixed reality game to investigate coordination in disaster response
[3]	FeedForward Neural Network-based Automated Learning Environment with Smart Education
[13]	LSTM-based Automated Learning Environment with Smart Education
[14]	Deep CNN-LSTM-based Managing Disaster Model with Smart Education
Our New Approach	Disaster Management Model based on a Hybrid of Deep CNNLSTM to enhance education

Table 6: Comparative Table Using Techniques and Methods in Models with Detecting and Fighting Fake News

Approaches	Methods
[32]	Deep Learning, Big Data and High Performance Computing to enhance Business and Marketing, while warying of Fake News
Our New Approach	Disaster Management Model based on a Hybrid of Deep CNNLSTM to enhance Detecting and Fighting Fake News

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 is one of the first to use multiple sources, namely Twitter and Facebook, for capturing messages during a crisis. Followed by the smart interface-based automated learning environment to improve disaster warning, while introducing smart education [2, 3]. While consists of an RNN-based Automated Learning Environment to improve awareness [12]. Based on LSTM it is to improve the lack of RNN of the previous model [12, 13]. 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 [39, 40].

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 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 $X1$, $X2$; X_t. Spatio-time sequence prediction predicts the most probable sequence of length K, given previous J observations (including the current sequence):

$$\hat{Y}t+1,\cdots,\hat{Y}t+K = \underset{\mathbf{X}_{t+1},\ldots,\mathbf{X}_{t+K}}{\mathbf{arg}\ \max}\ p(\mathbf{X}_{t+1},\ldots,\mathbf{X}_{t+\mathrm{K}} \mid \mathbf{Y}_{t-J+1},\ldots,\mathbf{Y}_{t-J+K}) \quad (1)$$

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:

$$e = (w1,\ldots,w_i,\ldots,w_n) \quad (2)$$

Containing words $w_i \in \mathbf{W}$, each coming from a finite vocabulary $\mathbf{V}$. $\mathbf{C}^n$ 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:

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

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

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

Therefore, the general formula is:

$$Error = -y * ln\ (p(x)) - (1 - y) * ln\ (1 - p(x)) \qquad (5)$$

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) [43]. The *fully-connectedness* makes them susceptible to overfitting information (See Figure 2).

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

[l−1] [l−1] [l−1]

nH nW nC

Conv(a[l−1],Kx,y(n)) = φ[l](X X X *Ki,j,k(a)* ∗ *a[xl+−i1]−1,y+j−1,k* ∗ *b[nl])* (6)

i=1 *j*=1 *k*=1

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

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

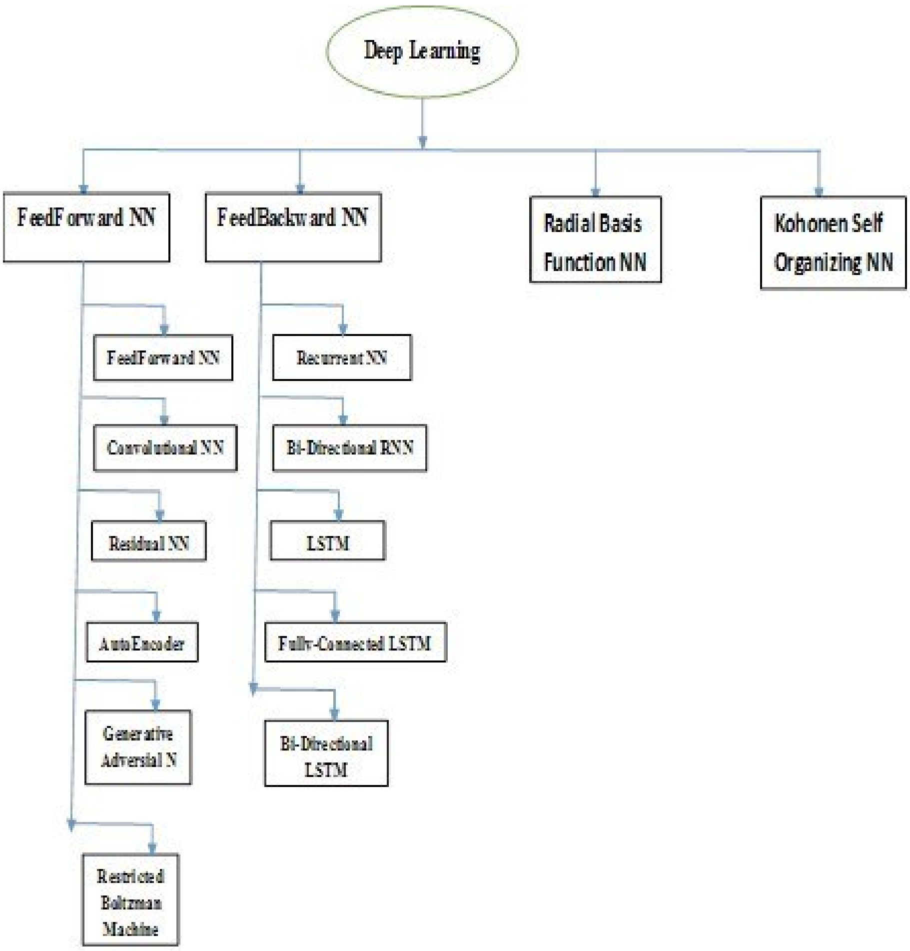

Figure 1: Classification Deep Learning Models

A Feedforward 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.

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 [11, 34]. 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, convolutionary networks (CNNs), are inspired by biological processes.

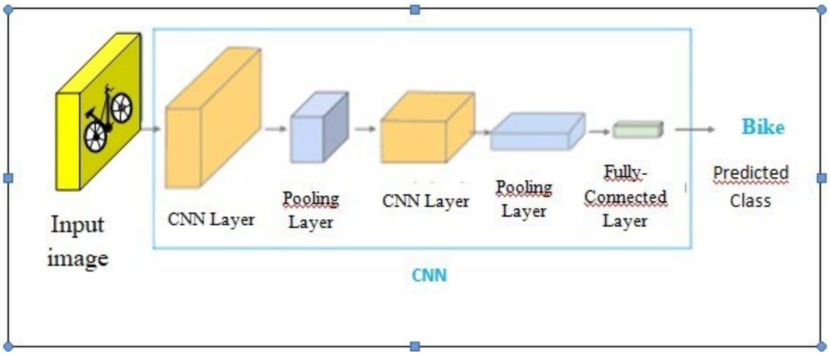

Figure 2: Convolutional Neural Network Structure (CNN)

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 [11].

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].

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 [11]. 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:

$$it = \sigma(\omega ix * xt + \omega ih * ht-1 + bi) \quad (9)$$

$$ct = ft * ct-1 + it * \tanh(\omega cx * xt + \omega ch * ht-1 + bc) \quad (10)$$

$$ft = \sigma(\omega fx * xt + \omega fh * ht-1 + bf) \quad (11)$$

$$jt = \sigma(\omega jx * xt + \omega jh * ht-1 + bj) \quad (12)$$

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

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

$h_t = f(h_{t-1}, x_t)$ Applying activation function tanh: (14)

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

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 funtion 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. $\boldsymbol{\sigma}_{hy}$ denotes the weight at the output state.

At each time step, all calculations necessary on the forward pass are:

$h_t = \alpha(\sigma_{hx} * x_t + \sigma_{hh}.h_{t-1} + b_h)$ (17) $y_t = \beta(\sigma_{yh} * h_t + b_y)$ (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:

• 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):

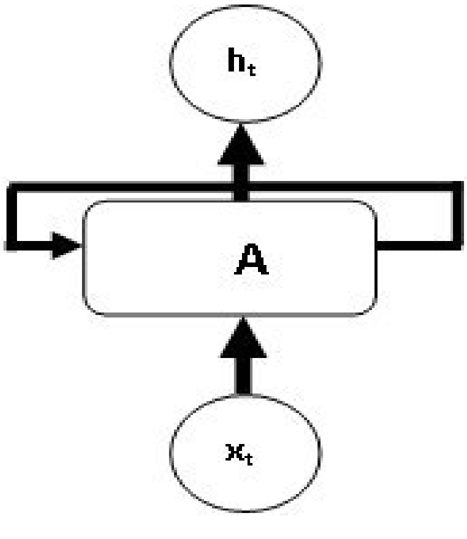

Figure 3: Overview of LSTM, its gates and activation functions

$$it = \boldsymbol{\sigma}(\omega ix * xt + \omega ih * ht-1 + bi) \quad (19)$$

$$ct = ft \odot ct-1 + it \odot \tanh(\omega cx * xt + \omega ch * ht-1 + bc) \quad (20)$$

• 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.*

$$f_t = \sigma(\omega_{fx} * x_t + \omega_{fh} * h_t-1 + b) \quad (21)$$

• 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.

$$jt = \sigma(\omega jx * xt + \omega jh * ht-1 + bj) \quad (22)$$

$$h_t = j_t \odot \tanh(c_t) \quad (23)$$

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 [48].

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

And tanh :

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

Proposed of Hybrid of Deep CNN-LSTM-based Model
The whole Deep CNN-LSTM modelling 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:

$$\epsilon = (\omega 1, \ldots, \omega_i, \ldots, \omega_n) \quad (26)$$

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:

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

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:

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

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

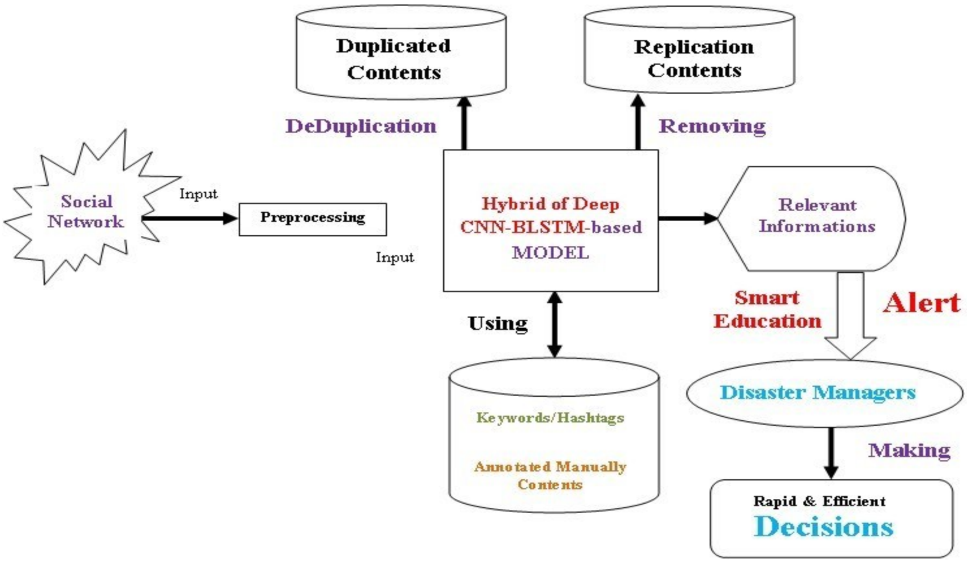

Figure 4: Functioning of Deep CNN-LSTM Model

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

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 $\mathbf{E}_K$ set. Figure 3 shows the functioning of the Hybrid of Deep CNN-LSTM-based Emergency Management.

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 [34].

This model is designed to support an introductory traineeship in disaster management for citizens, trainees and future disaster managers [3].

Therefore, 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.

Beginner Mode enables him, at any point, to ask it for generating (move on) the next step. Analysing 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, 12–14, 34, 39]: thereby
• Supporting example-based online help.

Educational messages play a role in raising awareness in times of public health crisis [14, 34].

This pandemic is becoming an infectious disease caused by the corona virus SARS-CoV-2.

Education about the Covid-19 [14, 34] 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, 12–14, 34, 39].

Health education and promotion can be integrated into curriculum-based or training-based programs as drills, modules, and visual media [10].

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 [14, 34]. it consists of standardizing good practice by developing the basic skills of essential knowledge and skills for health workers in disasters:

• 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 [14, 34].

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.

Information Security
Information security is due to the confidentiality, integrity, availability, nonrepudiation (concerning a transaction between several correspondents) and authentication of information [11-14]. 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 [32, 34].

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.

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 (key loggers), bots and human bots, [14, 32 and 34].

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, rumours, clickbait's, fabricated data (data breaches), and satire [32]. The spread of fake news has become a global issue that needs to be attended immediately [14]. Fake news is defined by as misleading content including conspiracy theories, rumours, and clickbait has, 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 behaviour, 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 [14]. 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 [32].

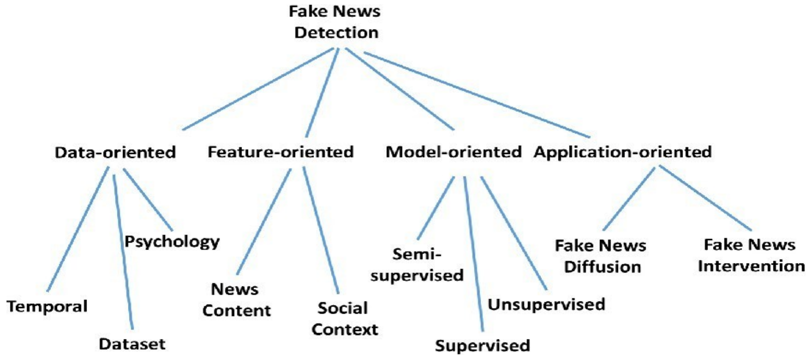

Figure 5: Taxonomy of Detecting Online Fake News

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 [34].

• 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 [34].
• 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.

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.

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 [34].

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 be influenced by the fake news [32].

Victim dynamics mean thoroughly understanding the details of the end user. The details can include age, gender, and 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 [14].

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 [6].

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', 'Wildfire 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. 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 unfavourable and dire situation at a certain time.

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	Bejaia Seism
Support Vector Machine (SVM) [34]	475
Neural Network [2]	531
Feed-forward Neural Network [3]	852
Recurrent Neural Network [12]	875
LSTM [13, 39]	908
Hybrid of Deep CNN-LSTM [14]	928
Our New Approach	991

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

Models	Oued Meknassa Flood in Chlef
Support Vector Machine (SVM) [34]	463
Neural Network [2]	501
Feed-forward Neural Network [3]	525
Recurrent Neural Network [12]	601
LSTM [13, 39]	657
Hybrid of Deep CNN-LSTM [14]	682
Our New Approach	695

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.

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

Models	Wildfire in Algeria
Support Vector Machine (SVM) [34]	1435
Neural Network [2]	1531
Feed-forward Neural Network [3]	2549
Recurrent Neural Network [12]	2734
LSTM [13, 39]	2804
Hybrid of Deep CNN-LSTM [14]	2911
Our New Approach	2943

Examples of Relevant Content of Wildfire in Algeria of August16^{th}–19^{th}, 2021 for a Set of Hashtags and Keywords from from multiple sources.

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

Models	Covid-19 in Algeria
Support Vector Machine (SVM) [34]	2364
Neural Network [2]	2495
Feed-forward Neural Network [3]	2634
Recurrent Neural Network [12]	2772
LSTM [13, 39]	2814
Hybrid of Deep CNN-LSTM [14]	2971
Our New Approach	2998

The contents are represented by a sequence of transactions T = ($t1,...,tn$) 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 Algeria2 , 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 [2], Feed-forward Neural Network [3], RNN [12], LSTM [13, 39] and CNN-LSTM [14] as this work, for Covid-19 in Algeria.

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 analyse it.

Table 11: Overview of Comparison between the Results Obtained In This Approach

Models	Bejaia Chlef Wildfire Seism Floods Algeria			Covid-19 Algeria
Support Vector Machine (SVM) [34]	475	463	1435	2364
Neural Network [2]	531	213	1531	2495
Feed-forward Neural Network [3]	852	525	2549	2634
Recurrent Neural Network [12]	875	601	2734	2772
LSTM [13, 39]	908	657	2804	2814
Hybrid of Deep CNN-LSTM [14]	928	682	2911	2971
Our New Approach	991	695	2943	2998

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.

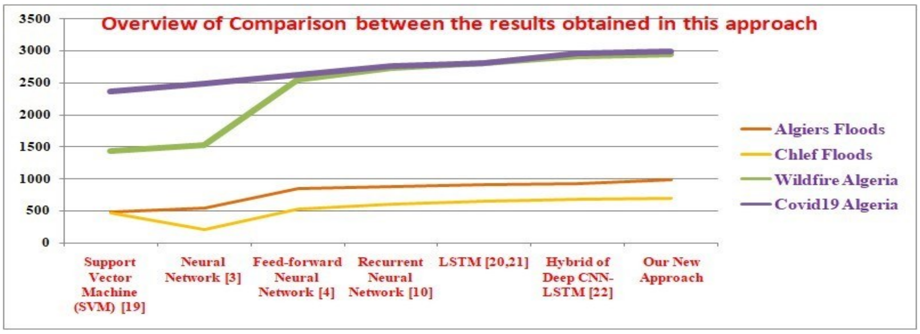

Figure 6: Overview of Comparison between the results obtained in this approach

Table 12: Overview of Comparison between the results obtained in this approach

Models	RMSE	MAE R^2
Support Vector Machine (SVM) [34]	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 [12]	13359.4722	19,962.5 0.4805
LSTM [13, 39]	16704.4894	19,557 0.5064
Hybrid of Deep CNN-LSTM [34]	21070.1960	12,809.5 0.6998
Our New Approach	58.7149	13789.75 0,9793

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 as humans do. Their second benefit is an inherent generalization power. This implies that patterns similar to are identified and answered to.

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 analysed in the following sections.

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

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 analysed 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 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.

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. Then the verification set checks the skill of these models.

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 hyperparameters), 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.

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

Models	RMSE	MAE R^2
Neural Network [2]	17 088.3797	18,471 0.3284
(FeedForward NN) [3]	16 100.9272	19,461.50.4645
(Recurrent NN) [12]	13 359.4722	19 962.5 0.4805
LSTM [13, 39]	16 704.4894	19 557 0.5064
Our New Approach	21070.1960	12.809.5 0.6998

To be fair, the number of relevant contents are taken as the historical information for NN, FFNN, RNN, LSTM and our new approach Deep CNNLSTM. 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.

Conclusion and Perspectives

All aspects of disaster risk management as it pertains to smart education for environmental sustainability were discussed in this study.

We aim to help communities better cope with disaster risk by investigating how global change affects population vulnerability to climate variability and extremes, and by exploring the role of higher education institutions in disaster risk management and climate change adaptation.

in terms of environmental sustainability, as well as the effects of climate change.

Based on a Deep CNN-LSTM hybrid, we have introduced an ad hoc real-time emergency management approach for warning, awareness, and education. Its purpose is to forestall disasters, whether caused by nature or by humans. It draws from a variety of sources and is built on a novel multi-tier capture methodology. When it comes to monitoring disasters, this method is helpful [44, 45]. Sharing information about oneself or one's status with the community is also possible. Help may also be accessed via it. Especially at a time of crisis, content might be produced in an informal style, devoid of grammar and logic, with plenty of noise, spelling mistakes, acronyms, etc.

Using certain keywords, only English text is retrieved from catastrophic events. Consequently, the dataset can include biases that are specific to certain domains. The same is true for material in languages other than English; there are many different kinds of reasons why it exists.

The emergency management model's characteristics have been created by analysing certain catastrophe material. There are a variety of disaster management models used by Algeria's emergency management, including Deep Convolutional NN-Bidirec-tional LSTM (Deep ConvBLSTM). When it comes to handling natural or man-made catastrophes, this one is only an expansion of our prior real-time warning models. In terms of emergency management, this is only the first step. Consequently, a reasonably robust and all-encompassing emergency model will be provided to users, mostly claim managers, among the viewpoints. All the other parts of disaster management, including prevention, preparation, and recovery, are going to be a part of our plan. We also want to use all Deep Learning hybrid techniques to improve automated learning [46, 51].

Many possible future works might benefit from this research. The initial step towards a better situation will be the verification of accurate information (while avoiding abusive data), the utilisation of various languages (especially French and Arabic), and the retrieval of helpful data to rescue individuals buried under the debris or to open roads at isolated corners caused by bridge damage or traffic jams. Incorporating Big Data into the real-time paradigm would also allow us to search for information on previous catastrophes, which might verify a warning that could eventually save lives in distress.

By incorporating the Enhanced Smart Education core unit as an online game called Smart Disaster, our goal is to create a learning environment that can automatically teach volunteers everything from content concept and satisfaction to alerts and all aspects of disaster management.

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Ethical Statement

Bejaia, August 07th, 2022 Zair Bouzidi University of Bejaia – Algeria On behalf of all authors, the corresponding author states that there is no conflict of interest.

This is done to serve and assert what is right. Zair Bouzid

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