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Faculté des Sciences et des Scineces Appliquées

Thèse de Doctorat

En Sciences

Option

Informatique

Théme

Social networks for Disaster management

Présentée par

Zair BOUZIDI

Devant le jury :

Akli	ABBAS	Président	MCA	Univ Bouira
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Réseaux sociaux pour la Gestion des Catastrophes

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Dedications

In memory of my dear father,

In memory of my dearest mother,

To my dearest wife Melaz,

To my adorable child Hanin, his wife Sabrina and their Dylan,

To my adorable daughter Sylia, her husband Ali and their cute little daughter Kawther,

To my adorable daughter Amel and her betrothed Mohammed Amine,

To my adorable daughter Leticia and her betrothed Sofiane,

To my adorable child Rayan,

To my brothers and sisters and their families (their children and their grandchildren),

To all the people I love and who love me,

I dedicate this modest work

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Finally, I would like to thank my colleagues from the University of Bejaia, notably those of Commercial Departement, who, in addition to always being available, I learn always with them and with their excellent advice.

Of course, I cannot end without thanking my relatives wholeheartedly and in particular my parents, begining with my wife, sons and daughters. who, during these years of thesis, have always supported and encouraged me, as usual...

Thanks to my parents for their patience and unwavering support which were more than essential to me throughout my studies. Unfortunately, they are no longer there to see the fruits of their efforts.

A special thank you to my wife Melaz who is always by my side during all these years of marriage, despite all the pitfalls of life.
Even if this thesis is a personal work, I would like to pay tribute here and express my deep gratitude to all those who, from near or far, have contributed to its realization and its outcome.

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Table of Abbreviations

Abbreviations	Meaning
AI	Artificial Intelligence
AIDR	Artificial Intelligence for Disaster Response
ANN	Automated Neural Network
API	Application Programming Interface
ARG	Alternative Realistic Game
BLSTM	Bi-Directional LSTM
BRNN	Bi-Directional RNN
CNN	Convolutional Neural Network
CNN-LSTM	Hybrid of Deep Convolutional NN and LSTM
ConvNets	Convolutional Neural Network
DM	Disaster Management
DL	Deep Learning
DOSN	Decentralized Online Social Network
FBNN	FeedBackward eural Network
FCLSTM	Fully Connected LSTM
FFNN	FeedForwark Neural Network
GAN	Generative Adversial Networks
GBED	Games based-Evacuation Drill
GIS	Geographic Information System
GPS	Global Positioning System
GSM	Global System for Mobile
HMD	Head-Mounted Display
IDS	Intrusion-Detection System
KDD	Knowledge Discovery in Databases

Abbreviations	Meaning
LR	Logic Regression
LSTM	Long Short-Term Memory
MDM	Motion Danger Map
MHM	Motion Hazard Map
ML	Machine Learning
MVC	Model-View-Controller
NB	Naive Bayes
NL	Neural Learning
NN	Neural Network
NSM	Non-Structural measures of Disaster Management
OCHA	Office of the Coordination of Humanitarian Affairs
OSN	Online Social Network
OSM	Open Street Map
P2P	Peer-to-Peer
POS	Par-of-Speech
PT	Penumbral Tourism
RBC	Rule-based Classifier
RBF	Radial Basis Function NN
RBM	Restricted Boltzman Machine
ResNet	Residual Neural Network
RF	Random Forest
RNN	Recurrent Neural Network
SM	Structural measures of Disaster Management
SNS	Social Network Site
SR	Symbolic Regression
SVM	Support Vector Machine
TED	Tsunami Evacuation Drill

Abstract

Neural networks-based Alert Model is used to retrieve, in real time, social networks (Twitter and Facebook) contents. Once cleaned of duplicate and replication content, we want to learn, from the first-hand content, thanks to manually tagged information, relevant content to warn and alert people and disaster managers in order to make quick and efficient decisions that will save lives.

Keywords **:** Disaster, Neural learning, Relevant content, Social media.

Résumé

Le modéle d'alerte basé sur les réseaux de neurones est utilisé pour récupérer, en temps réel, les contenus des réseaux sociaux (Twitter et Facebook). Une fois nettoyés des contenus dupliqués et répliqués, nous voulons apprendre, à partir du contenu de première main, grâce à des informations étiquetées manuellement, un contenu pertinent pour avertir et alerter les personnes et les gestionnaires de sinistres afin de prendre des décisions rapides et efficaces qui sauveront des vies. Il est amélioré en environnement d'apprentissage automatisé basé sur Deep Learning pour récupérer de tout le Web. Il est également amélioré pour devenir un hybride d'un ALE basé sur CNN-LSTM profond utilisant la sensibilisation, l'évaluation et l'éducation. Des expériences ont montré qu'il continue à donner de meilleurs résultats que les travaux précédents.

Mots-Clés **:** Catastrophe, Apprentissage neuronal, Contenu pertinent, Média sociaux

مُلَخَّص

نَسْتَخْدِمُ آلنَّمُوذَجَ آلْمُعْتَمِدَ عَلَىٰ آلشَّبَكَاتِ آلْعَصَبِيَةِ لِلإِسْتِرْدَادِ مُحْتَوَيْ آلشَّبَكَاتِ آلْعَصَبِيَةِ (تْوِتِرْ وَ فَيْسْبُكْ) فِي آلْوَقْتِ آلْفَعَّلِي. بِمُجَرَدِ تَنْظِيْفِ آلْمُحْتَوِيْ آلْمُكَرَّرِ، نُرِيْدُ آنْ نَتَعَلَّمَ، مِنَ آلْمُحْتَوَيْ آلْمُبَاشِرِ، اِسْتِنَادًا عَلَيْ آلْمَعْلُومَاتِ آلَتِىْ تَمَّ وَضْعِ عَلَامَاتٍ عَلَيهَا يَدَوِيًا، وَ آلْمُحْتَوَىْ ذِي آلْصِلَّةِ لِتَحْذِيرِ وَتَنْبِيهِ آلاَشْخَاصِ وَمُدِيرِي آلْكْوَارِث مِنْ آجْلِ آتِخَاذِ قَرَارَاتٍ سَرِيعَةٍ وَفَعَاْلَةٍ، مِنْ شَـ■ـهَا آنْ تُنْقَذَ آلاَرْوَاحِ. تَمَّ تَعَزِيزِ هَذَا آلْعَمَلِ، اَوَّلَا وَقَبْلَ كُلِ شَيٍ، مِنْ خِلَالِ تَطْوِيرِ بِيئَةَ تَعَلُّمِ مُتمِتَةٍ تَعْتَمِدُ عَلَيْ آلْتَعَلُّمِ آلْعَمِيقِ لِلْتَعَاْفِي مِنْ كُلِّ آلْوِيبِ وَ آلْتَعَلِيمِ آلْذَكِي فِي حَالَاتِ آلْكَوَارِثِ. ثَانِيًا، يَتِمُّ تَحْسِيْنِ هَذَا آلْنَمُوذَجِ مِنْ خِلَالِ دَمْجِ هَجِينِ آلْذَاكِرَةِ طَوِيلِ آلْمَدَيْ وَطَوِيلِ آلْمَدَيْ لِشَبَكَةٍ عَصَبِيَةٍ تَلَافِفِيَةٍ عَمِيقَةٍ مَعَ آلْوَعْيِ آلْظَرْفِىْ وَتَقْيِيمِ آلْكَوَارِثِ وَالْتَعْلِيمِ. اَظْهَرَتْ آلْتَجَارُبِ آنَّ يَسْتَمِرَّ فِي آلاَدَاءِ بِشَكْلٍ آفْضَلِ مِنَ آلْعَمَلِ آلْسَابِقِ.

كَلِمَاتٌ مِفْتَاحِيَةٌ : آلْكَوَارِثِ، اَلْتَعَلُّمِ آلْعَصَبِىْ، اَلْمُحْتَوَىْ آلْمُرْتَبِطِ، اَلْشَّبَكَاتِ آلاِجْتِمَاعِيَةِ

بِسْمِ ٱللَّهِ ٱلرَّحْمَٰنِ ٱلرَّحِيمِ

سُبْحَانَكَ لَا عِلْمَ لَنَا إِلَّا مَا عَلَّمْتَنَا إِنَّكَ أَنْتَ ٱلْعَلِيمُ ٱلْحَكِيمُ.

صَدَقَ ٱللَّهُ ٱلْعَظِيمِ

General Introduction

Introduction

Large-scale disasters have become, in recent years, more frequent all over the world. Earthquakes of Boumerdes [1] of May 21, 2003 and Chlef (Algeria) of 1980 (7.3 degrees on the Richter scale) caused 2,633 dead and collapse of 20,000 homes. Every time a disaster occurs, many people recognize the importance of disaster management. Most disasters have huge and lasting impacts for human live and society. Disasters such as earthquakes, floods, explosions, acts of terrorism and tsunamis result in human suffering, property loss and other negative consequences [2]. To minimize the consequences of these events, it is essential to prepare and develop resilient communities by educating them with the appropriate and up-to-date information needed to cope with disaster. Here, we will see how individuals, organizations and communities develop skills in response to unforeseen events (in preparation, disaster management or institutional aspect). Our analytical framework is guided by a vast activity curious about important social phenomena and observations of this evidence that occur in virtually every disaster. Indeed, at each event, harmless it may be, people come running to share it with other people, particularly those who are connected. May this event be happy and even more so if it is an unfortunate event.

Motivations

Social networks are used to post status updates in multiple forms, like: text messages, images and videos. Online information is useful for a quick response in crisis event, according to numerous studies [3]. Social networking use analyzes in times of crisis have identified a distinct role for local (field) event users, more likely to enhance situational awareness, by generating useful information [4]. Thanks to the improvement of storage technics, ease of use, participatory culture and end-user interoperability (Web 2.0), we are facing an information overload, notably the Web disseminating information in interactive way. It is notably immense, diverse and dynamic. This new era is a period of developing rapidly knowledge. Traditional learning measures are no longer able to cope with the increasingly complex and rapidly changing situation of the new knowledge society. Therefore, a new vision of learning is needed: Automated Learning. Its purpose is to discover, in large amounts of data, valuable information to understand this data an predict future data behavior. This process can be statistical, mathematical or using AI techniques to check large amounts of data (stored in warehouses or, notably, in streaming). This knowledge, could be known at first, may be correlations, patterns or general trend in the data.

Methodology

Automated Learning consists of analyzing problems to understand their principles and develop ping appropriate mathematical models. Experimental data must be used to verify, the system correction or the estimation of some difficult parameters, to mathematical modeling [5]. A fundamental shift is needed, towards a more open and learner-centered learning model, where Automated Learning uses various manual and automatic tools: we begin by describing the data, summarize their statistical attributes, visualize them using curves, graphs, diagrams, and finally look for significant links potential between variables (as repeated values). But the data description alone does not provide a action plan. We must build an information discovered-based prediction model, and validate this model on other data. It is argued that automated learning could meet the new knowledge society needs and transform learning.

However, in the majority of cases, systems do not have principles understood or are too complex for mathematical modeling. Automated Learning, suggesting complex and unimaginable impacts on societies and broadly economies, remains primarily in computer science field, but closely linked to cognitive science, neuroscience, biology and psychology. It could lead to crossroads of systems, nanotechnology, biotechnology and cognitive science, leading to artificial intelligence with a wider core.

Smart education plays a key role in encouraging community members to develop managing disaster skills. Besides, members also share their knowledge and help, one another, in preparedness, like with other education techniques, namely, Games Based-Evacuation Drill [6], Evacuation drills, Paradigmatic Tourism [7], Mixed or Alternative Realistic Games [8], Penumbral or Dark Tourism, and tower defense game [9], or other evacuation techniques (Simulations).

In this research work, we present the theoretical, design, implementation and evaluation details of an environment, a learning framework. Main objective of this last is helping users to become familiar with different learning models using, in this environment, a wide available variety of media and digital data. This neural learning-based automated learning environment is, before all, fundamentally dynamic, ubiquitous, flexible, social, distributed and personal.

Organisation of the manuscript

This manuscript is organized as per the following description scheme (Figure 1):

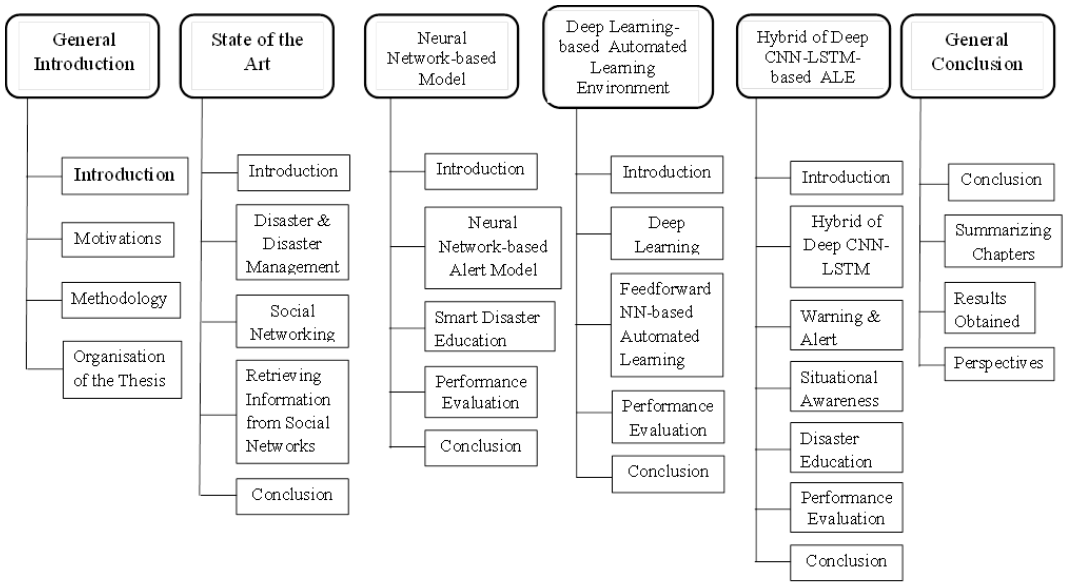

Figure 1: Organization of the Thesis

The overview of disaster and disaster management models is presented in the Chapter 1. First of all, this chapter recalls the modelisation of disaster, after presenting all its definitions. This mathematical modelisation of disaster and disaster management allow the researchers to have an idea of different aspects and concepts necessary to save lives.

In Chapter 2, we present our basic implementation of the first alert model based on automated neural network for extracting relevant content from Twitter and Facebook using keywords and hashtags of disaster management. This Chapter allows us to begin designing et implementing the heart of the automated learning environment.

The chapter 3 represents the first enhancement of the automated learning environment. It is based on deep learning, namely Feedforward Neural Network and allows extracting, in real time, information on catastrophic events from multiple sources (all the Web): it immediately alerts disaster managers to make quick and efficient decisions that could save lives. Indeed, we propose a new ad hoc real-time alert model for the management of disaster, whether natural or anthropogenic, based on a new multi-view recovery model from multiple sources. It is very interesting and useful method for monitoring, not only disasters, but also crowds or an happy or unhappy event necessitating quick and efficient decision.

Chapter 4 presents an other improvement of our real-time automated learning environment by integrating a Hybrid of Deep Convolutional LSTM neural network, as specified by Abiodun et al. cite Abiodun2018. So, with the richness and in particular the specialization of the different Deep Learning models, we design our own model according to our own needs

A science is any discipline in which the fool of this generation can go beyond the point reached by the genius of the last generation.

Max Gluckman

Chapter 1

State of the Art of Retrieving relevant contents of Disaster from Social media

Summary

1.1 Introduction

THIS work deals with the problem of extracting relevant information from social networks in crisis event. It begins by presenting conceptually disaster and disaster management, followed by the presentation of social networks and the different models used to extract the relevant information of a possible disaster.

Then, it presents a classification of all the mathematical models used for extracting relevant information, from SVM to neural learning. It consists of integrating artificial intelligence technologies, social media, disaster management and neural learning. It consists of an automated learning environment based on an extension of the real-time alert model used for the management of natural and anthropogenic disasters that integrates encapsulations from multiple sources and retrieves information by combining multiple research results. This experience provides a backdrop for our automated learning environment and provides for it some great ideas.

Finally, this work ends by summarizing the main features of this approach, providing some references to related work, and discussing some issues related to artificial intelligence, social media and disaster management.

1.2 Disaster & Disaster Management

1.2.1 Disaster

Catastrophes, as tsunamis, wildfires, floods, earthquakes, terrorist attacks, result in human suffering, property destruction, etc. Besides, several anthropogenic catastrophes have arisen recently, primarily due to substantial technological growth, interconnected networks and globalization. Terrorism and ecological terrorism, biological risks and product forgery include anthropogenic catastrophes [10, 11]. The planet suffered several major natural and / or anthropogenic disasters of all time in recent years. Natural, seismic, hydrological, geological or biological processes, as cyclones, earthquakes, tsunamis, floods, wildfires, landslides, sandstorms and volcanic eruptions or hydro-meteorological paroxysms (*exceptional precipitation*), pandemics (*Covid'19 coronavirus pandemic and its famous variants: Delta or Mu*) [12] or human processes, as simple precipitation, are often modified by species. Indeed, the SARS-CoV-2 version (VUI 202012/01 renamed VOC 202012/01) has emerged rapidly from south-east England since September 2020, and many questions continue to arise. Dozens of other nations, including Europe[1], have reportedly identified the variant. Table 1.2 gives an overview of recent natural and anthropogenic disasters, and their damage.

We have 160,000 dead and 60 million injured in 27 years (from 1980 to 2017), with only serious damage from 2012 to 2017 (i.e. five years) with 32,454 dead, 3,355 injured, 6,639 missing, more than 83,000 hectares burned, 350 homes destroyed and significant damage. Recent threats from these disasters reaffirmed urgency and significance of loss estimation, and need of decision support resources. To fulfill needs and requirements, multiple disaster management models [2, 6, 11, 13, 14, 15, 16, 17, 18] have been studied

[1] https://www.cdc.gov/coronavirus/2019-ncov/transmission/variant.html

Table 1.1: Latest catastrophic events.

No	***Catastrophic event***	***Period***	***Damage***
1	WildFire Haiti	Oct 2007	230,000, 220,000
2	Earthquake of California	Jan 2010	203 deaths, $6,152.9\ Km^2$ ravaged lands
3	Floods of Thailand	Jul 2011	815 Dead
4	Tsunami earthquake of Japan	Apr 2011	15,896 dead, 6,157 injuries, 2,537 missing
5	Hurricane Sandy of USA	Oct 2012	220 Dead
6	Typhoo Haiyan of Philippines	Nov 2013	26,626 injuries
7	Elbe flood of Germany	Jun 2013	25 dead
8	Subway bombing of Russia	Apr 2017	15 dead, 50 injuries
9	Suicide bombing of England	May 2017	22 Dead, 116 injuries
10	Three explosions in Indonesia	May 2018	9 dead, 40 injuries
11	Japan Floods	Jun 2018	235 dead, 13 missing
12	Earthquake of Indonesia	Sep 2018	2,000 dead, 1.5 million injuries
13	Earthquake Fire of Haiti	Oct 2018	18 Dead, 548 injuries
14	Terrorist Attack of Strasbourg	Dec 2018	5 dead, 10 injuries
15	Kivu Ebola epidemic of Congo	Aug 2018-Jun 2020	14,739,450 affected, 1,162 healed, 2,299 dead
16	Coronavirus Pandemic COVID-19	Jan 21^{st}-Jul 23^{rd}, 2020	14,739,450 affected, 8,332,461 healed, 610,776 dead

and built. Some of the major disaster management activities are notably hazard evaluation, risk management, mitigation, preparedness, response and recovery. When disaster strikes, people seek information and ways [10, 15, 16, 17] to provide data and assist those in need. With altruism inspired by disasters, individuals support those in distress or suffering. Information on protecting people, goods and aid sources, are the most common forms of online assistance in crisis event. As a consequence, study and experience in disaster management frequently refers to the formula 1.1 [11] of the following type:

$$\mathbf{R} = \mathbf{D} * (\mathbf{V} - \mathbf{Res}) \tag{1.1}$$

Where **R** is the risk that is the likelihood or expectation of a failure, **D** is a danger that is a risk-threatening situation. The vulnerability **V** is the extent to which individuals or objects are likely to be affected; and the tools **Res** are the assets in place that decrease the effects of hazards.

Disaster is defined [19] as a complex problem that must be approached with a multidimensional and cross-platform framework for gathering information. It is characterized as a severe disruption to the functioning of society [20] that involves extensive losses to humans, materials or the environment. Figure 1.1 shows the classification of various disasters. Disaster is simple if the community structure is intact, and composed if community structure and function are disrupted.

While disaster avoidance is not feasible, the likelihood of a disaster can be reduced by managing risk and vulnerability and enhancing individuals and communities' capacity to resolve these risks, in accordance with the previous formula (1). Disasters may differ in terms of types and impacts on human communities through knowing the source of common danger [11]. It is possible to classify disasters into two major categories: natural and anthropogenic. Natural disasters consist of disasters that are geophysical, biological and hydro-meteorological. Anthropogenic disasters consist of acts of terrorism, simple accidents and accidents involving technology. The threat, vulnerability and capability relationship is generally defined by the formula 1.2 [11] as follows:

$$\mathbf{Dis} \ = \ \mathbf{D} \ * \ (\ \mathbf{V} \ / \ \mathbf{A} \ ) \tag{1.2}$$

Where **Dis** is the disaster, **D** is the danger to the disaster, **V** is the vulnerability to danger and **A** is the ability to overcome a disaster. This equation clearly shows that the risk of disaster for a community increases because of the high probability of a disaster (*danger*) and its inability to cope with the disaster. However, the use of adequate knowledge, skills and resources for disaster phases of preparedness and response can counteract the overall risk of a disaster.

Catastrophes are events that are fast-paced. Slow and chronic social disruptions [15], however, are important to theorize as catastrophes because they can have a greater effect than rapidly caused disasters.

Recently, many disasters have emerged in addition to existing ones, mainly anthropogenic catastrophes due to considerable technological development, interconnected networks and globalization [2], [16], [17]. Anthropogenic catastrophes include terrorism, ecological terrorism, product forgery and biological threats. Figure 1 shows catastrophe examples with type, location, year and victims number.

Recent catastrophe threats have reaffirmed the urgency and importance of loss assessment and needing decision support tools.

Impossible preventing disasters, but their risks can be minimized by controlling vulnerability and improving the individual and communities capacity to overcome them. Understanding the source of common danger, disasters can vary in terms of types and impacts on human societies [11], [17]. Disasters can be classified into two main categories : natural and anthropogenic. Natural disaster include geophysical, biological and hydro-meteorological disasters. Anthropogenic catastropher consists of terrorist acts or simple and technological accidents. Figure 1.1 shows new disaster classification.

Disaster, due to a technical or human failure and occurred in a dangerous facility for environment protection, namely a factory, a depot, a site, a quarry and damaged a large number of real estate, is said technological. Among these technological disasters, there are nuclear disasters and industrial disasters. Industrial disasters can be the result of negligence or incompetence, or any combination of these factors. These can usually result in more or fewer deaths, injuries or disappearances, as well as significant property damage. These consequences can be immediate or delayed. A nuclear disaster is a serious accidental industrial event, the consequences of which are related to the presence of radioactive materials. Figure 2 shows Global assessment of the Covid-19, as July 19^{th}, 2020.

Terrorism is a crime against human life in violation of national and international laws while having a political purpose that would influence or change the policy of a country by terrorizing its civilian population.

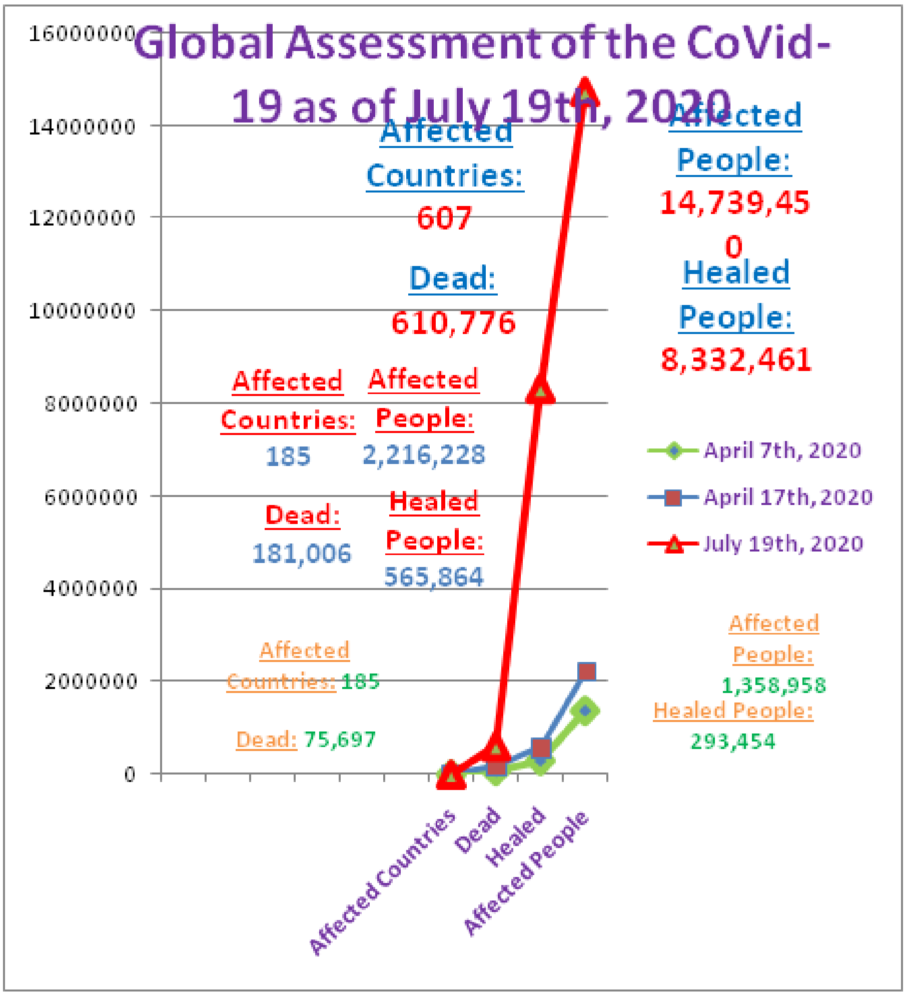

Figure 1.1: Punctual assessment worldwide of the Corona Virus pandemic, C0VID-19.

Disasters are events that are fast-paced. Slow and chronic social disruptions[15], however, are important to theorize as disasters because they can have a greater effect than rapidly caused disasters.

In crisis event, people seek ways and information to provide help to others. With the altruism promoted by the crisis, people come to the aid of people in difficulty or suffering. Most common types of online help in crisis event are in the form of

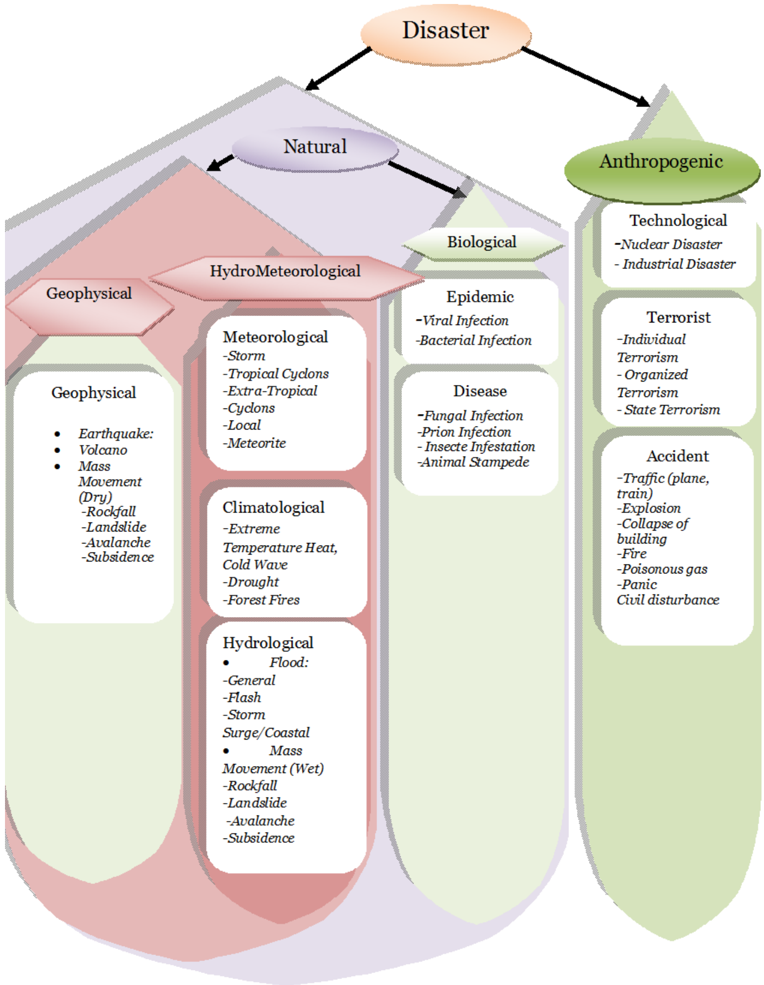

Figure 1.2: Our new classification of disasters.

information on people and goods safety, more faster and frequent than that of official reports. This equation clearly shows that the risk of disaster for a community increases because of the high probability of a disaster (danger) and its inability to cope with the disaster. However, the use of adequate knowledge, skills and resources for disaster preparedness and response can counteract the overall risk of a disaster.

1.2.2 Disaster management

Stages of disaster recovery cycle are prevention, warning, planning, action, mitigation and restoration. In disaster management, there are at least six key elements [21]: Prevention, Mitigation, Planning, Response and Relief, Restoration and Reconstruction. The process of disaster management, however, is defined in four phases, namely: [22] mitigation (before disaster), [21] preparedness (before disaster), [22] response (during disaster) and [21] recovery (after disaster).

Urgency, significance of loss estimation and needing decision support resources,

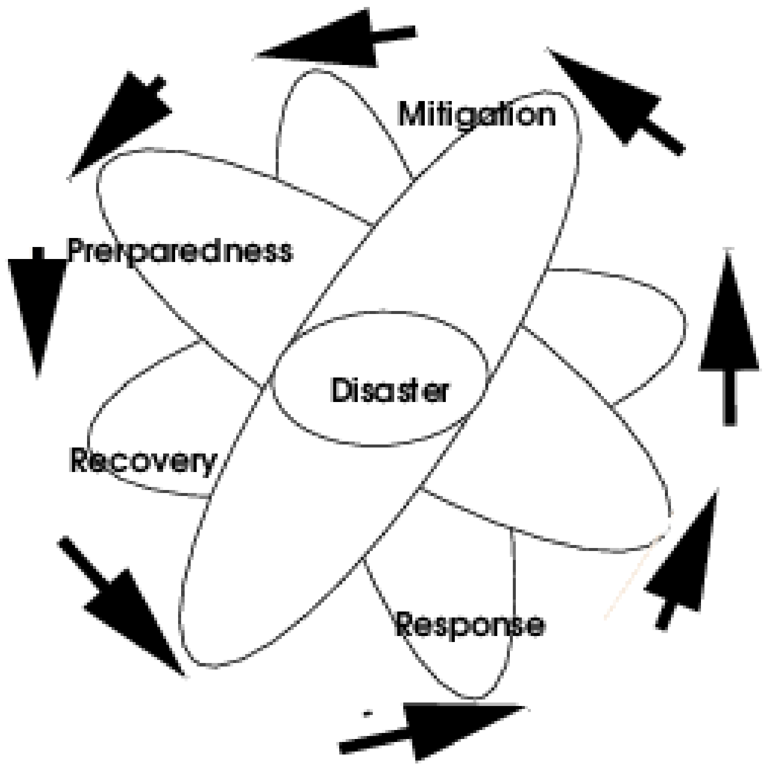

Figure 1.3: Disaster Management Cycles

were reaffirmed by recent disaster threats. In order to fulfill these needs and requirements, various models for disaster management [2, 6, 11, 14, 15, 16, 17, 18] have been studied, designed and developed. Some of major disaster management activities are preparedness, hazard evaluation, mitigation, response, recovery and risk management.

The emergency management is defined in four phases, namely [17] : mitigation (before disaster) [22], preparedness (before disaster) [20], response (during disaster) [22] and recovery (after disaster) [11], [20] (see Figure 1.3).

- Mitigation (pre-disaster): is the process of planning and taking action to reduce long-term risks to people and property in the event of a disaster [23]. This eliminates the risks before a disaster occurs.

- Preparedness (before the disaster) : is planning how to respond to a disaster [21].

- Response (in case of disaster) : consists of conducting an situational assessment and implementing strategies developed in preparation phase [23]. It responds to victim needs and take the necessary steps as public warning, safe evacuation, managing persons or victims, measures to restore the basic life structure and short-term plans for restoring daily life normalcy [2].

- Recovery (after a disaster) : is about ensuring that all community activities and systems return to the normal situation [22]. Thsese actions can be classified into two main categories, namely short-term recovery and recovery.

Disaster management is roughly categorized into two types [6, 17] namely structural measures (SM) and non-structural measures (NSM). SM can reduce physical damage directly related to disasters (eg. embankments, seismic buildings and evacuation sites). However, they are expensive, time-consuming, and can not necessarily mitigate the damage caused by unexpected events. NSM are based on practice or knowledge ; they can provide people with disaster management motivation and knowledge of at a relatively low cost (evacuation drills, policy and law development, and education).

1.2.3 Disaster Management Models

This theoretical chaos has fueled divergences and some variations between the different disaster management models, leading to complications. While the scope of disaster management calls for templates to be used, [24]. Well-formed[25] typology can be useful in eliminating complications and maintaining discipline, in a chaotic environment. As for Disaster Management, the Classical Model, Computer Model and Disaster Management Social Networking Model are as follows:

1.2.3.1 Classical Disaster Management Model

By preventative measures, we can reduce the seismic risk, starting with the citizen's knowledge by teaching him the attitude to take before, during and after the earthquake. Then, we continue with reducing the seismic vulnerability of buildings to restrict the damage. All this must be done with the cooperation between all the volunteers (solidarity action). Part of the popular wisdom of disaster management is that communication and collaboration be facilitated by personal familiarity, not just institutional contact.

Collaboration. For coping with natural and technological threats, disasters and the effects of terrorism, collaboration is an essential base. The disaster management field and profession is also developing into a more collaborative enterprise. The following equation models the collaboration:

$$\mathbf{DM} \rightarrow \mathbf{CE} = \mathbf{VC} - \mathbf{D} \tag{1.3}$$

with :

$$\mathbf{VC} = \{ VC_i \} \; with \; \mathbf{i} \in [1 , \mathbf{N}] \tag{1.4}$$

Where:
DM denotes Disaster Management,
CE denotes Collaborative Entreprise,
VC denotes set of Volunteers Contents and
D denotes the set of Content of Volunteers in Double and
VC_i denotes the $\mathbf{i}^{st}$ Volunteer Content.

This evolution has increasingly shifted from top to bottom beyond the classical bureaucratic model to become a more complex and versatile [26] network model that promotes multi-organizational, intergovernmental and intersectoral cooperation. The partnership between all the volunteers as we see it is shown in figure 1.4.

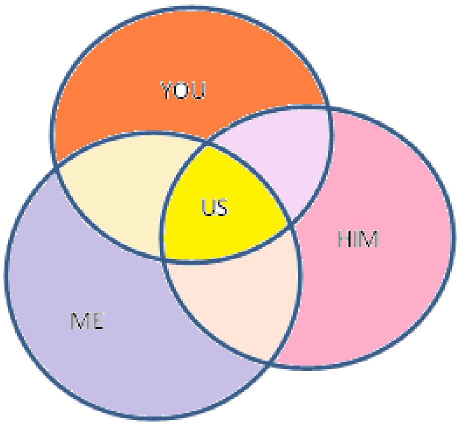

Figure 1.4: Collaboration.

In disaster management, coordination is so critical, and command and control methods are so problematic that it becomes a monumental challenge to establish and maintain the required ties, and even a necessary task when dealing with disasters. This capacity is strengthened by regular engagement, including involvement in planning and training exercises. Collaboration has always been a skill for us [26] because of the use of volunteerism and community participation. Volunteers provide leading-edge capacity and links to community resources. Organizational and individual volunteer mobilization often serves a social and psychological purpose: it brings people together and gives them a sense of effectiveness. Organizations will be enabled to learn and promote adaptation and improvisation by more adaptive leadership.

Coordination. A multitude of social and behavioral research poses coordination as a significant obstacle for people, associations and organizations responding to disasters [27]. Furthermore, for emergency management preparation, coordination and knowledge sharing between various teams are prerequisites [27]. Channels of communication developed during the mitigation process serve as a basis [27, 28] for meaningful coordination and contribute to improving inter and intra-organizational resilience and cooperation and plays a big role in disaster risk reduction.

Dissemination of information. Transmit and/or exchange relevant information containing daily *updates* instead of a particular *warning* about a disaster, such as *weather updates*, *traffic alerts* and *news*. These types of data help [27] to keep people aware of their climate.

Issue warnings. In addition to daily 'information notifications' [27, 28], accurate and timely warnings play an important part in disaster management.

Communication. In all phases of disaster management, contact between community members remains important in terms of communication. They interact with each other during the mitigation process, whether for keeping in contact or helping each other to plan: they must communicate during disasters (*or just after disasters*) to update their status and share about disaster ravages [15]. Besides, there is evidence that in most disasters, local communities and authorities affected are the best ones to respond immediately. As a consequence, in emergency operations, the local group plays a critical role.

Moral / emotional support. One of the key roles of the media during and after a disastrous incident is to respond to the needs of people for emotional support, camaraderie and group ties. Individuals are actively seeking media emotional support [15], which provides isolated members of the group up to the time span identified by the impact of the event. Supportive action [15] is illustrated when people gather to express their gratitude to disaster responders and offer moral support to disaster victims.

1.2.3.2 Computer Model for Disaster Management

Damage evaluation is the main criteria to understand the situation for considering devastation nature and preparing the relief accordingly, notably with integrating important humanitarian principles [29] into the requirement design of an information system. This must promote producting disaster management skills with, for instance, simulations or education.

Disaster Education Disaster education plays a critical role in motivating community members to improve disaster management skills. [16] In schools, industries and neighborhoods, evacuation exercises are also performed.

Also, there are *Games Based-Evacuation Drill* (GBED) [6] drills of evacuation operating with mapping of motion hazard (MHM) on a tablet with a GPS receiver and smart devices as tablets and smart glasses. In disaster situations, virtual children have different reactions [30], while adults (*ie, HMD carriers*) are required to provide these virtual children with sufficient evacuation instructions while looking at situations of virtual disasters. Disaster Education Based Services [16, 31], as Paradigmatic Tourism: PT) that integrates Games Based-Evacuation Drill (GBED) and Black Tourism as a place-based disaster education., are other game-based evacuation exercises (*GBED*). Penumbral Tourism (*PT*) [32] is a place-based disaster education that uses disaster simulation in the real world.

A disaster fantasy game based on Tangible Bits [33] is developed. Tower defense game [9] improves ability to prepare for floods, to evacuate a three-dimensional virtual (*3D*) world [34], immersive environments of virtual reality [35], Head-Mounted Displays (*HMD*) and other platforms [36]. Players can learn how to organize disaster response in Geo-fencing MRG[8]. As for GBED, when traveling to an evacuation location, participants often view digital documents on a portable computer, including electronic tablets and smart glasses.

Simulations Advanced models and broad data analyses have led to innovative disaster management methods being developed by visualizing disaster incidents that have not yet been realized.

Using Motion Danger Map (*MHM*) and smart devices, the tsunami evacuation drill (*TED*) framework [6] is built by simulation by configuring tsunami simulation using Google Maps. Street flooding causes were discovered by observing, road profiles and flood simulations [37]. Suitable solutions were suggested.

An environment of multi-method simulation for humanitarian supply chains [38] is planned, prototyped and evaluated to create detailed models of relevant humanitarian supply chains to support decision-making process of humanitarian actors. Floods caused by short and abundant showers [37] have been analyzed and other variables have been defined using topography derived from light detection and telemetry (*LiDAR*), simulations of floods, to find inexpensive solutions to traffic problems created by floods.

1.2.3.3 Social Networking Model for Disaster Management

In general, the media plays a very significant role in disaster management. In the various stages of crisis management, the didactic role of the media differs only in content. During planning stage, people seek risk information, not preparedness. During the impact process, during this scary moment, they get emotional support from the media, and connections to the outside world that break the isolation. The media focuses on the hardest hit areas after the catastrophe, provides estimates of damage and losses, and assistes communities in their reconstruction efforts. For recovery, after the impact, they want to know the conditions of the other communities. However, it is difficult to understand these voluminous and high velocity data, requiring crowdsourcing, crowd tasking and Collaborative Management.

Collaborative Disaster Management Large paper maps still have obvious advantages in some cases, as response, combination high resolution and portability: it is called geo-collaboration [39], a community work enabled by geo-spatial information technology on geographical scale problems.

A geo-collaborative, Web-enabled framework [40] is designed to target the unique characteristics of mobile and ubiquitous computing environments enabling to promote promote visualizing, asynchronous and online interaction between actors, while promoting distributed spatial and temporal cognition.

Crowdsourcing and Crowdtasking in Disaster Management There is an evaluation of advantages of social networking models and work-sharing networks in disaster management (information collection, quasi-journalistic editing and crowdsourcing). A method to develop a computing environment based on community acts as a real-time dashboard for government agencies responsible in monitoring populations during disasters, thanks to motivational analysis fof assessing the most likely essential app features to optimize continued user interaction (See figure 1.2.3.3).

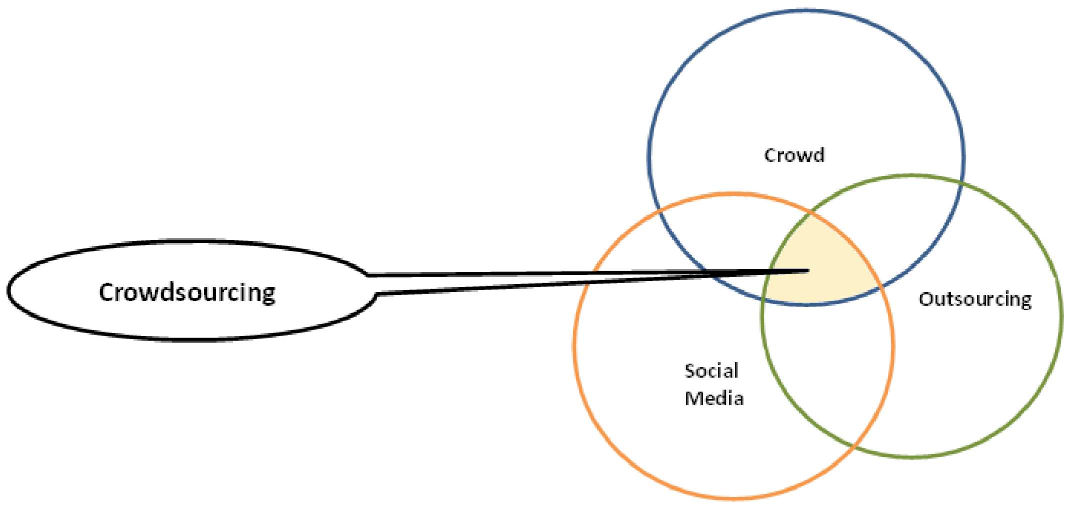

Figure 1.5: Crowdsourcing.

The continued engagement of its users is measured by the performance of these community-based computer systems such as eBayanihan [41].

Crowdsourcing [41] can be a feasible production instrument that shows that extrinsic motives far outweigh extrinsic motivations (such as monetary reward).

In many occasions, the merits of unaffiliated volunteers have been shown. Tools such as Ushahidi[41] allow people to quickly access relevant information, as geographical position-based reports on crisis events and community needs.

To simulate involvement in crisis events, the motivation of volunteers in a serious gambling scenario is significant.

For crisis management, computerized application guidance systems [42], known as known as public safety systems, enable rapidly organizing public emergency services, save lives and property.

In recent years, a growing number of studies have examined the use of social networking data to gain knowledge of areas of human activity as diverse as the detection of disease as epidemics [43] and predicting the stock market. Social networking has emerged as a potential resource for improving natural or anthropogenic disasters [44]. To reduce their impact on humankind, the various management tasks during all phases of disasters [45] have growing information needs centered on the human being to facilitate better decision-making with a view to reducing loss of life and property. Social networks, which record a large amount of human activities, have attracted more and more attention from researchers [46]. Thus, their use, including micro-blogging such as Twitter, has spread, especially during disasters. Social networking is analyzed according to the four dimensions (*space, time, content and network*) [45] while summarizing the common techniques for extracting these dimensions and proposing some methods accordingly. While Dat Tien Nguyen & al. [47] introduce classification methods based on the neural network to identify tweets useful during a crisis situation.

Different social networks have different characteristics and are therefore more or less suitable for use during disasters depending on the phase [20] and the type of disaster. As Joao Porto de Albuquerque & al. [44] who present an approach to improve the identification of relevant social networking messages based on the relationships between geo-referenced social networking messages as voluntary geographic information and the geographical characteristics of data derived flood phenomena authoritative. As for the intensity of the earthquakes from information of the people who undergo them, the information [48] are compared with the 'reports' of markers and Tweets. Social networking such as wikis and collaborative workspaces are used to manage the 2010 earthquake in Haiti as the primary knowledge-sharing mechanisms [27, 49]. To locate survivors in a collapsed building and on fire, a new method [50] is proposed for indoor location in a building that collapses and burns with a disaster.

For coordinating relief activities from information from real-time Tweets, an alert system, which is based on Twitter, effectively managed complete disaster information because of its speed of communication, its reach and the quality of information [6]. The AIDR (*Artificial Intelligence for Disaster Response*) system combines human intelligence and artificial intelligence to categorize crisis-related messages in the event of sudden onset of disasters [3, 46]. Finally, for the exploration of social networking data, several techniques [51] could be described to make Twitter data more usable by emergency services and explore what information can be extracted from Tweets. A social networking image processing pipeline that combines human intelligence and artificial intelligence [52] captures and filters the content of social networking images and extract exploitable information during an ongoing crisis event through a hybrid crowdsourcing and machine learning approach. Social networking image processing system (Image Act) [18] aims to classify the images content, and to help humanitarian organizations to understand the situation and start rescue work. A comprehensive conceptual approach to geo-collaboration is applied to a range of prototype systems that support both identical and different group activities [53]. Another generic coordination architecture targets, in particular, the specific characteristics of the mobile and ubiquitous computing environments that are required for collaborative applications [40]. While Brian M. Tomaszewski [54] & Alan M. MacEachren [53] developed a geo-collaborative, The work of Simone Wurster & al. [55] provides an approach for evaluating the benefits of work-sharing systems in disaster risk reduction. While Amisha M. Mehta & al. [56] have identified and evaluated three models of social networking use in disaster management, namely: information gathering, quasi-journalistic editing and crowdsourcing.

However, a new method of designing a community-based computing environment involves integrating information in the field into eBayanihan [19] which is Web-based for citizen reporting in addition to collecting information in social media. Michael Middelhoff & al. [41] aim to test the usability and acceptance of various methods and tools facilitating crisis communication via multiple channels. Jasmin Pielorz & al. [57] proposed the use of Open Street Map (*OSM*) driving distance instead of the previously used flight distance that better reflects the interests of volunteers and first responders. On the other hand, computerized application guidance systems, known as public safety systems, are used for disaster management to quickly coordinate emergency public services and save lives and property [42].

In post-disaster relief operations, it is assumed that all fixed cellular infrastructures do not be functional. The adaptability of P2P networks [58] must be exploited to respond to the characteristics of disaster situations. Peer-to-Peer networks have been used to interconnect field workers by just one active connection between a peer and the control room to perpetuate the disaster management system [59]. Due to the large autonomy of the peers involved leading to self-regulation behavior, such networks are very well prepared to address frequent changes in topology [60], information and positions. Rohit Sonawane & al. [61] used Wi-Fi peer communication in disaster management by developing an Android or iOS application that supports Peer-to-Peer Wi-Fi technology by enabling communication with others in disaster situations. Increasing availability of mobile data communications and Internet access in mobile networks enable Peer-to-Peer applications from the wired network to be available to mobile users [60].

M. Mecella & al. [62] developed a software infrastructure to support human operator collaborative work, with handheld devices, in crisis event (*PDAs*) and collaborating to achieve common goal: the whole team executes a process (*macro-processes*) and the different teams (*of different organizations*) collaborate, combining various processes.

M. Bortenschlager & al. [59] to voluntarily interconnect in the field with a single active connection to the peer to peer sustain the claims management system. The data centers in the local network by thePAs, as to get from the geo-collaborative. They proposed to integrate Peer-to-Peer (*P2P*) concepts into Geo-Collaborative applications. This is a new prototype, a new concept is available in a new strategy to replication replication self-document to self to context.

Pradnya Mate & al. [63] developed a BitTorrent-like application for ad-hoc wireless networks on Android mobile phones. Except that, it is better to use small segments for downloading in order to have an increased parallelism with several peers involved. In addition, to maintain the quality of service of this application when transmitting data, they are considering future improvements.

A. Bhatnagar, et al. [64] implement a peer-to-peer protocol for priority message delivery to respond quickly to alert messages by creating a distributed phonebook for controlled message delivery and a response handling framework appropriate for alert messages. Certain restrictions remain necessary for networking, high dependence on the GSM operator, no possibility of dynamic role allocation, high performance allocation of a general-purpose mobile device, use of a method presumed based on the security policy of intensive messages.

R. Sonawane & al. [61] developed an Android or iOS application that supports Wi-Fi technology for free communication with others in the event of a disaster. This Wi-Fi Peer-to-Peer can be used in areas affected by a server, it allows users to search the network and available services before the connection. Unfortunately, this could cause interference during communication.

1.2.3.4 P2P Model for Disaster Management

Peer-to-peer (P2P) is a decentralized computer network model: the transactions that take place there take place between equally accountable nodes [58]. It is possible to exploit the adaptability of P2P networks [58] to meet the characteristics of disaster situations.

Figure 1.6 demonstrates the peer-to-peer network used to interconnect field staff to maintain and/or perpetuate the disaster management system [59] using a single active link between a peer and the control room. In these geo-collaborative implementations [59], P2P principles have thus been implemented.

In disaster management, there is also an Android or iOS application and an Android chat application [61] using Wi-Fi peer communication that supports Peer-to-Peer Wi-Fi technology by allowing communication in disaster situations with others.

The advantages of applying the P2P model [59] have been extended to the Disaster

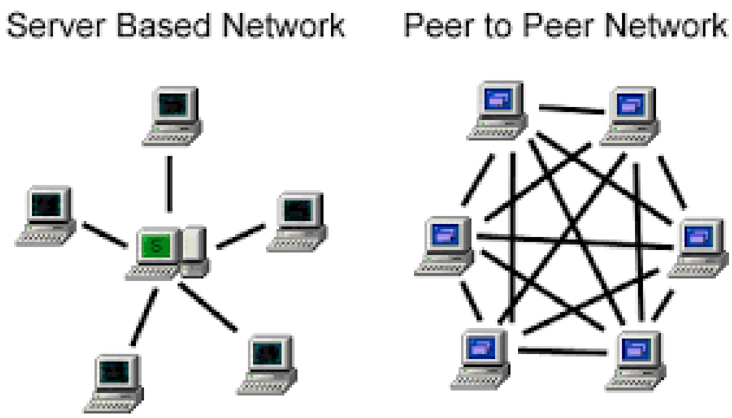

Figure 1.6: Comparison between Server-based Network and Peer-to-Peer Network

Management Geo-Collaboration as an alternative to GIS's most common client/server approaches and suggest the interconnection of P2P networks with mobile operators.

Usually, wireless resources are scarce and differ in efficiency and availability, restricting the use in mobile environments of peer-to-peer applications.

Mobile P2P systems are a relatively new approach to integrating P2P principles with mobile computing technologies such as WirelessLAN, Bluetooth and telecommunication networks such as GSM, GPRS or UMTS [40], with over-frequent traditional changes in wireless settings that tend to be a challenge to conventional peer-to-peer systems. In the design of P2P systems, mobility support is becoming an increasingly important research subject.

To avoid this situation from lasting and growing, exchanging data on disaster situations should rapidly monitor the disaster. IoT/M2M network [65] is suggested to be paired with P2P cloud service to provide results as social services, such as SNS, for quick and smooth response in the event of a disaster with the eventual delay caused in the current commercial network. One active link between one peer and the control room at a time is sufficient to perpetuate the disaster management mechanism and increase the GeoCollaborative's availability.

P2P [66] algorithms for resource-limited and irregular (with no pre-existing infrastructure) WAHNs allow performance, scalability and fault tolerance to be achieved, where a spatially correlated group of nodes have crash simultaneously.

1.2.4 Discussion about Disaster Management Models

Different models for disaster recovery by academics and organizations have been suggested. Despite their success in some areas, disasters still pose a major challenge to sustainable growth. According to Nojavan et al. (2018) [67], which calls it *the strategic management*, the proposed study typology showed that the comprehensive model should include all models due to the complementarity between them.

Qualitative vs Quantitative comparison. It may sound like the more accurate of the two is the quantitative method. But no. Qualitative risk analysis is very suitable for assessing likelihood and easily prioritizing risks by assessing severity in a broader sense. It also makes it easier to recognise areas that need special attention, and can also be used to manage risk in real-time at any point of the project. That being said, there is an undeniably stronger combined approach[2]. Essentially, there are two sections of a single whole that allow you to assess *risk* comprehensively *risk level* of individual activities within the project schedule.

Disaster recovery consists of a layer of packages with subsystems. In order to provide scalable and extensible architectures, modular design unifies interfaces and data sharing. 3D visualization thus increases the interpretability of disaster data [68] and the efficacy of decision-making processes.

As for Disaster Education[6, 8, 9, 16, 30, 31, 33, 34, 35, 36, 69, 70, 71], Simulation[32] and Crowdsourcing[72] on Twitter only, there are several applications for Disaster Management in the Alert / Mitigation process. [14] on Twitter and Facebook for Forecasting and [15, 16, 17, 69] on all the Web and finally for Collaboration [26]. We also have in Preparedness phasis for Situational Awareness [69, 72, 73, 74, 75, 76] and for Damage Assessment [74, 75, 76, 77] on only Twitter and in Response phasis for Post-Disaster Coordination [68, 76]. In Recovery phasis, we have no application (see Table 1.3).

1.2.4.1 Complementarity between Disaster Management Models

Multiple models are proposed for managing disaster by agencies and researchers. Despite efficiency in some locations, catastrophes are still a fundamental challenge in environmental sustainability. Nojavan et al. (2018) [67] select the strategic management in the final phase as the global or overarching theme. While the proposed study typology showed that the comprehensive model should include all mentioned elements because of the complementarity between models.

1.2.4.2 Comparison between Disaster Management Models

Qualitative vs Quantitative comparison. Which is better for disaster management approaches? Based on that description alone, it might sound like the quantitative approach is the more reliable of the two. But that is not the case. By ranking severity in wider terms, qualitative analysis of risk is ideal for gauging probability and prioritizing risk in easy way to understand. It also enables identifying areas requiring

[2] 09^{th} Dec 19 Posted by Richard Wood Topics: Plan Risk Analysis

special attention, and even, can be employed at any stage of the project to manage risk in realtime. A combined approach is unquestionably stronger, essentially, they are two parts of a single whole, enabling you to comprehensively determine *risk level* of individual activities within the project schedule[3].

1.2.4.3 Modular Architecture of Disaster Management

Disaster management system consists of a layer of subsystems packages. The modular design used in the Disaster management system unifies interfaces and data exchange to provide flexible and extensible architecture. For instance, Subsequent 3D visualization enhances the disaster data interpretability and decision-making processes effectiveness [68].

1.2.4.4 Some Existing Disaster Management Packages

Many applications exist on Disaster Management in Warning / Mitigation phasis as for Disaster Education[6, 8, 9, 30, 31, 33, 34, 35, 36, 69, 70, 71], Simulation [32] and Crowdsourcing [72] on only Twitter, for Forecasting [14, 78] on Twitter and Facebook and [15, 16] on all the Web and finally for Collaboration [26]. We also have in Preparedness phasis for Situational Awareness [72, 73, 74, 75, 76, 79, 80] and for Damage Assessment [74, 75, 76, 77, 80] on only Twitter and in Response phasis for Post-Disaster Coordination [68, 76]. But no application in Recovery phasis.

1.3 Social Networking

Recent trends in using social networking highlight increasing users number of social networking applications, as well as a significant increase in the such applications number.

1.3.1 Online Social Networks

In a short time social networks have invaded the daily lives of Internet users and Web professionals. Social media giants Twitter and Facebook were seen evolving, growing and establishing. They have been followed by a multitude of other more specific networks[4] : Instagram, LinkedIn, etc The list is long. Social networks are essential reservoirs for the development of a disaster-stricken community, providing its members with a social history of past survival behaviors, social capital to cope, ways of assessing disaster risk and an effective means of transferring disaster-related

[3] 09^{th} Dec 19 Posted by Richard Wood Topics: Schedule Risk Analysis
[4] https://www.blogdumoderateur.com/chiffres-reseaux-sociaux/

information, especially with the arrival of decentralized social networks (DOSN) with a high guarantee of confidentiality and security. Among the existing research studies, a group of studies identifies useful social networking information [4], using machine learning, to successfully extract structured information from unstructured textual Twitter messages. People use social networks to post situational updates in different forms [81] as videos, images, messages and text. Numerous studies [3, 82] have shown that this online information is useful for rapid response in disaster management. For example, after major disasters, researchers use Twitter data to know the number of people injured or dead [4], the most urgent needs affected people (*shelter, food, water, etc.*), donations, etc. Communication via social networking is direct, easy and instant and can simplify quick responses. Custom sites like Facebook, Twitter, Instagram, YouTube and Xing can subjectively offload the first contact [83] of authorities and service providers in crisis with strangers. These analyzes of using social networks in catastrophes identified a distinct role for local users of event (*or 'in the field'*), whom are likely to generate useful information to enhance situational awareness [84]. Social networks can be considered as a practical and efficient emergency communication tool. While the predominant social networks function remains social interaction, their sites are considered fourth popular emergency information source. The main objective of this research is to study the utility of social networking during disasters from the point of view of citizens. Various social networks have different features and are therefore more or less suitable for use during disasters depending on the phase and the type of disaster. Social networking can support the exchange of information before, during and after a disaster in many ways. For example, disseminate timely alerts, publish regular updates on disaster and inform on available resources. The period before a disaster may also include activities such as gathering information from the public about potentially vulnerable regions or demographic groups. With the proliferation of social media, knowledge about disasters is transformed from expert knowledge to everyday knowledge co-produced by various stakeholders thank to Web 2.0. The social networking can increase public awareness of different forms of contingency, placing it in the context of disaster knowledge, in light of the diverse needs of local communities.

In recent years, a growing number of studies have examined the use of social networking data to gain knowledge of areas of human activity as diverse as the detection of disease as epidemics and predicting the stock market. Social networking has emerged as a potential resource for improving natural or anthropogenic disasters. With regard to quantitative spatial and temporal analyzes, most of the existing work has sought to make sense of social networking data as an autonomous source by analyzing aggregated models. As Albuquerque (de) J. P. & al. [44] who present an approach to improve the identification of relevant social networking messages based on the relationships

Table 1.2: Social media-based disaster management software or packages in different phases.

Disaster Management Actions	Disaster Management Phasis with Social Media Applications
	1. Warning/Mitigation
Disaster education	[6, 8, 9, 16, 17, 30, 31, 33, 34, 35, 36, 70, 71]
Simulation	Social Networks Model via a: only Twitter: [32] b: Twitter & Facebook: / c: The entire Web:
Forcasting	Social Networks Model via a: only Twitter: b: Twitter & Facebook: [14] c: The entire Web: [15, 16]
Collaboration	Social Networking Model: [26]
Crowdsourcing	Social Networks Model via a: only Twitter: [72] b: Twitter & Facebook: c: The entire Web :
	2. Preparedness
Risk assessment and reduction	Social Networks Model via a: only Twitter: / b: Twitter & Facebook: / c: The entire Web :
Situational Awareness	Social Networks Model via a: only Twitter: [72, 73, 74, 75, 76, 86] b: Twitter & Facebook: / c: The entire Web :
Damage Assessment	Social Networks Model via a: only Twitter: [74, 75, 76, 77, 86] b: Twitter & Facebook: / c: The entire Web :
	3. Response
Post-Disaster Coordination and Response	Social Networks Model via a: only Twitter: [68, 76] b: Twitter & Facebook: / c: The entire Web :
	4. Recovery
Normal Activities Resumption	Social Networks Model via a: only Twitter: / b: Twitter & Facebook: / c: The entire Web :

between geo-referenced social networking messages as voluntary geographic information, the geographical characteristics of data derived flood phenomena authoritative (*sensor data, hydrological data, and digital elevation models*) and very challenging biomedical data that is usually large, noised and imbalanced [85]. As for the intensity of the earthquakes from information of the people who undergo them, the information are compared with the 'reports' of markers and Tweets describing the same events to determine the intensity of the earthquakes and found a strong correlation between these two sources of information. Also, slip reports, produced by people filling out a Web form, arrive in a time frame similar to that of Tweets, although there are many more Tweets available. Social networking such as wikis and collaborative workspaces are used to manage the 2010 earthquake in Haiti as the primary knowledge-sharing mechanisms.

To locate survivors in a collapsed building and on fire, a new method is proposed for indoor location in a building that collapses and burns with a disaster by first estimating the two-dimensional attenuation distribution or three-dimensional in terms of the wireless signal used for localization, called the 'attenuation map', using wireless tomography based on compressed detection. They finally locate a target node using the estimated attenuation map. For coordinating relief activities from information from real-time Tweets, an alert system, which is based on Twitter, effectively managed complete disaster information because of its speed of communication, its reach and the quality of information. The AIDR (*Artificial Intelligence for Disaster Response*) system combines human intelligence and artificial intelligence to categorize crisis-related messages in the event of sudden onset of disasters. This system, which exploits information from Tweets in real time from a disaster area to help coordinate relief activities, is now commonly used by the UN Office for the Coordination of Humanitarian Affairs (OCHA) and many other emergency services around the world [87].

Finally, for the exploration of social networking data, several techniques could be described to make Twitter data more usable by emergency services and explore what information can be extracted from Tweets. Images displayed on social networking platforms in crisis event are analyzed to determine the damage level caused by catastrophers. A social networking image processing pipeline that combines human intelligence and artificial intelligence [52] captures and filters the content of social networking images and extract exploitable information during an ongoing crisis event through a hybrid crowd-sourcing and machine learning approach. User-generated content on social networking in disasters is useful for disaster management and crisis response. On the other hand, an end-to-end social networking image processing system called Image4Act aims to collect and classify the content of images posted on social networking platforms, and to help humanitarian organizations to become aware of the situation and to launch relief operations. However, understanding voluminous and high velocity data is very difficult.

This section presents relevant related works, namely information retrieval models, and particularly those from several sources, and alert models.

These are sites for sharing feelings, as Facebook, Viber, Twitter, Messenger, etc. The knowledge available on social networks differs from other web sources in several respects. Such messages use less formal language: words from more than one language, with different errors in grammar and spelling, unstructured, fuzzy and short-lived. Their length and content vary considerably [88]. We detected emotions using four types of features : interjections, blasphemy, emoticons and the general feeling of the message, which are widely used by individuals to convey emotions such as danger, surprise, happiness, etc. For identifying these caracteristic types, we used a combination of par-of-speech (POS) tags, compiled lists of interjections and blasphemies on the Web for French and English and patterns of regular expression for emoticons. From online platforms monitored by Online Listening Tool, as Radian6 or one of its rivals [14, 15, 16, 17, 88, 89, 90, 91, 92] content can be gathered from websites to all social media.

In fact, via Application Programming Interface (API) [16, 17, 88, 89, 91, 92] many networking platforms allow access to their data. The model, fairly representing the essentials, is generated by online listening instruments, namely : harvesting contents, cleaning the data of non-informative information, enabling relevance thanks of learning corpus obtained with tagged messages, and analyzing results.

1.3.2 Listening and Monitoring Online Social Media

Contents were collected from online channels tracked automatically by Online Listening Tool, namely Radian6 [92] or one of its competitors, as Awario, Brand24.com, Brandwatch, Mention, Keyhole, Socialert.net, SocialPilot.co, Simplify360, etc. from social media, such as LinkedIn, Instagram, Google+, Twitter, Facebook, Youtube and so on. Many networks platforms enable accessing to contents via Application Programming Interface (API) [88]. Online listening tools provide the model, which reasonably represents the essentials, namely: *harvesting contents* (such as conversations at the social media, news or any information in the Web), *cleaning the data* of duplication and replication content, *enabling relevance* (thanks to the neural learning, obtaining of relevant information with the learning corpus obtained thanks to the tagged messages) and *analyzing the results* (verification and analysis of the results).

Social networks are an important part of the online activities of web users. There are two types of social networks : Centralized social networks and Decentralized social networks. Current OSN are Web services, running on logically centralized infrastructure [94]. They use content distribution networks and distribute part of load by caching, while keeping a central repository for user and application data. This centralized nature of Online Social Networks has several drawbacks including scalability, privacy, dependence on a provider, and need for being online for every transaction [95]. Web sites have millions of users every day. DOSN (Decentralized Online Social Network) is a distributed social network system with little or no dependency on a dedicated core infrastructure. [94], a solution to data leaks thanks to the P2P architecture [96].

Recent trends in using social networks highlight increasing user number of social networking applications as well as increase in number of such applications. Rapidly, social networks have invaded the lives of Internet users and professionals. The social media giants Facebook and Twitter were seen establishing, growing and evolving. They have been followed by a multitude of other more specific networks : Instagram, LinkedIn, etc. People use social networks to post situational updates in various forms [81] as images, messages, text and videos. Numerous studies [3, 15, 16, 17, 97] show that content is useful for a quick response to a particular event. Communication via social networks is instant, easy and direct, and simplify responses. Clean pages such as Facebook, Twitter, Instagram, YouTube and Xing can subjectively ease the initial contact of authorities and service providers. These analyzes of using social networks in crisis events have identified a distinct role for users, whom are likely to generate useful information to enhance situational awareness [97]. Social networks can be considered as a practical and efficient emergency communication tool. While the predominant function of social networking remains social interaction, these sites are also considered the fourth most popular source of information. Various social networks have different features and are therefore more or less suitable to use in given situation. Social networking can support the exchange of information before, during and after an eventual event. With the proliferation of social media, knowledge is transformed from expert knowledge to everyday knowledge co-produced by various stakeholders thank to Web 2.0 [16, 17]. Recently, a growing number of studies examined using social networks data to gain human activity areas knowledge as diverse as the disease detection as epidemics and predicting stock market. However, understanding voluminous and high velocity data is a difficult.

Table 1.3: Comparative table of all techniques and methods used in Models.

Ref	**Identification Methods**	**Used OSN**
[70]	Flood Disaster Game-based Learning	Twitter
[71]	Educational Purposes at the Higher Education Faculty with Special Reference	Twitter
[74]	summarization with social-temporal context	Twitter
[75]	Capitalize on a TREC lead to create a tweet summary dataset	Twitter
[76]	semi-automated artificial intelligence-based classifier for Disaster Response	Twitter
[86]	Summarization of Situational Tweets in Crisis Scenarios: An extractive-abstract Approach	Twitter
[14]	Based on Artificial Neural Network	Twitter & Facebook
[15]	Based on ANN	The entire Web
[16, 17]	Based on FeedForward Neural Network (FFNN)	The entire Web
[93]	Based on Recurrent neural network (RNN) trained with Long Short-Term Memory (LSTM)	The entire Web

Content was collected from all online channels followed by online listening Tool, namely Radian6 [91, 92] or any its competitor, such as Awario, Brand24.com, Brandwatch, Mention, Keyhole, Socialert.net, SocialPilot.co, Simplify360, etc. from websites to social media, as Facebook, LinkedIn, Twitter, Instagram, Google+, Youtube and so on. Actually, some network platforms enable accessing to contents via APIs (Application Programming Interface) [88]. Online listening tools provide the model, which reasonably represents the essentials, namely, as shown in figure 1.7 :

1 - Collecting content: as social media conversations, news, or any other information on the Web ;

2 - Cleaning data of duplication and replication content ; eliminating, from it, any dubbed information like retweet, and any information harmful or redundant ;

3 - Enabling relevance : thanks to the neural learning, obtaining of relevant information using learning corpus obtained thanks to tagged messages, done by volunteers, and

4 - Analyzing results: The verification and analysis of results is carried out for ensuring adequacy to build disaster information such as damage assessment, situational awareness and/or education.

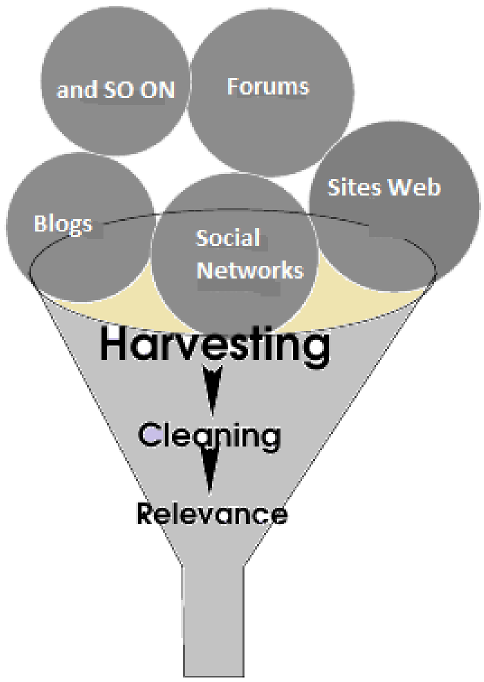

Figure 1.7: Online Methodology Reflecting our Listening and Monitoring Approach.

Benefits of using Facebook and Twitter APIs include :

1 - the use of the development space of the two social media ;

2 - encouraging development environments ;

3 - the scientific recognition of development environments ;

4 - encouraging other social media to involve themselves in research development ;

5 - helping social media to feel imbued with this desire for development and scientific research in parallel with their commercial activity, and

6 - contributing to development of further improvements in networking services.

1.4 Information Retrieval Models from Social Networks

In a bilingual recovery, comparable document-aligned data [98] is used to easily learn patterns of common topics or word concepts. However, the preparation of comparable documented data requires a lot of human involvement and time. Therefore, such approaches are not appropriate when information about an ongoing event should be retrieved quickly. The work of Joseph A. Shaw and Edward A. Fox [99] focuses on methods for recovering separately from different sources and then combining them using data fusion techniques. Multi-view recovery based on deep learning, attempting to learn document embedding in a space, with no difference between various data sources. Unfortunately, this approach has low performance scores for all method used : indicating the problem difficulty and requiring better methods. According to Cynthia D. Balana [100], Google Crisis Response's (GCR) National Risk Management and Disaster Response Board (NDRRMC) had integrated Facebook and Twitter into its surveillance system and website for a quick response.

Whether it is Twitter, Facebook, Viber, Messenger, any forum or any thing in the Web, these are platforms where people often express emotions. Emotions are detected using four types of features, namely : interjections, blasphemy, emoticons, and the general feeling of the message.

Emoticons blasphemies and Interjections are widely used by individuals to convey emotions as happiness, surprise, danger, etc. For identifying features types, a combination of POS tags is used in the English tagger, compiled interjections lists and blasphemies on the Web for English and regular expression patterns for emoticons.

1.4.1 Relevant Information Retrieval from Social Media

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). Tweets produced during the Elbe flood in June 2013 in Germany [44, 101] are examined, using only, statistical analysis to identify general spatial patterns in the flood-related tweets occurrence associated with the floods proximity and severity. Comparable document-aligned data [98] are used to easily learn patterns of common topics or word concepts, in a bilingual recovery. However, the preparation of comparable documented data requires a lot of human involvement and time. Such approach is not appropriate if an ongoing event information must be retrieved quickly. Distributed situation awareness reports based on Twitter [72] activity during natural disasters are captured. We will study all artificial learning methods, from machine learning to deep learning, after an overview of retrieving relevant knowledge techniques.

1.4.1.1 Classification Models

In Automated Learning, we distinguish regression problems from classification problems. Thus, we consider that the problems of predicting a quantitative variable are problems of regression while the problems of predicting a qualitative variable are problems of classification. Certain methods, such as logistic regression, are both regression methods in the sense of predicting how to belong to each of the classes and classification methods.

The performance of this system strongly depends on the selection of the appropriate model. We are now trying to select the most appropriate model for our proposed feature set based on specific criteria. Our learning approach is based on four advanced classification models for the feature set above, namely : We will study all retrieving relevant knowledge techniques on social networks, from Support Vector Classification, Random Forest Classification to Neural Learning.

1. Support Vector Machine: To solve regression problems, the approach used for support vector classification can also be expanded. Learning points beyond a limit are not taken into account in cost function to build support vector classification model. Thus, building a support vector classification model depends only on a subset of training data [102].

2. Random Forest: To control over-fitting and increase predictive precision, Random forest generates many decision tree based on random data and variables collection and and takes the averaging notion. Trees, in the lot, are developed from training set using bootstrap sampling. If a node is split in tree creation, selected split is not the best between all features, but it is the best split between a random features subset. Thus, the bias of the forest usually increases, but also decreases due to techniques such as averaging its variance, compensating more than increase bias [103]. It is part of machine learning techniques, used in data mining and machine learning, and refer to a method based on a decision tree as a predictive model. Decision Tree Forests combine the concepts of random subspaces and bagging. The algorithm performs learning on various decision trees driven on slightly different data subsets.

3. Logistic Regression: It is a binomial regression model that best models a simple mathematical model with many real observations. Used in machine learning, it is a special case of generalized linear model. Logistic regression or logit model

is a binomial regression model. It is best to model a mathematical model with many real observations, as all binomial regression models. For associating with a vector of random variables $(x_1, ..., x_K)$ a binomial random variable generically noted y. Logistic regression, special case of a linear model, is widely used in machine learning.

4. Symbolic Regression: It consists in obtaining mathematical functions using a finite sampling of the values of independent variables and the associated values of dependent variables. Thanks to the artificial bee colony programming algorithm (ABCP) and recently the automatic multi-tree artificial bee colony programming algorithm (MTABCP), which remains on the association of the ABCP programming method and least squares, this method is used in Machine Learning. Symbolic regression constructs mathematical equations by composing both parameters and equational forms. In other words, it attempts to derive non-linear equations by simultaneously manipulating equational shapes and parameters while solving a given modeling problem. The symbolic regression method aims to find the best combination of variables (inputs and outputs), symbols and coefficients in order to develop an optimal model satisfying a set of fitness cases. The problem of symbolic regression can be considered as an optimization problem in order to find the best function of the variables, symbols and coefficients satisfying a performance criterion.

5. Naive Bayes: The Bayesian naive classification implements a naive Bayesian classifier belonging to the family of linear classifiers. A more appropriate term for the underlying probabilistic model could be *statistically independent model*. Naive Bayesian classifiers can be trained efficiently in a supervised learning context, according to each probabilistic model nature. Naive Bayesian classifiers were efficient in many complex real world situations, despite *naive* design model and simplistic basic assumptions. In 2004, an article showed that there are theoretical reasons behind this unexpected effectiveness. However, another 2006 study shows that more recent approaches (reinforced trees, random forests) provide better results. Naive Bayesian classifier advantage is requiring little training data to estimate parameters necessary for classification, namely averages and variances of different variables.

6. Rule Based Classifier: The rule-based classification term can be used to refer to any classification system using IF-THEN rules for class prediction. Classification schemes published on rules generally include the following components :

   - Rule induction algorithm consisting of the process of extracting the relevant

IF-THEN rules from the data ;

- Rule classification measures : referring to certain values used to measure the usefulness of a rule to provide an accurate prediction. Rule ranking measures are used in rule induction algorithm to eliminate unnecessary rules, improving efficiency. Besides, they are used in class prediction algorithm to rank rules to be then used for predicting the class of new cases.

We follow a simple approach : if any of the features mentioned above are present in content, we mark it as relevant. Table 1.4 presents the set of features for the content extraction task.

We follow a simple approach - if any of the features mentioned above are present in a content, it is marked as relevant.

Table 1.4: The set of features for the content extraction task.

No	Descriptions
1	*Slang expressions. Example* : *Bail*, *Feeling blue*, *Buck*, *By the skin of* (*my / your / his / her*) teeth, Creep (*n.*), *Couch Potato*, *Cram*, *Crash*, *Down to earth*, *Drive up the wall*, *For Real*, *Going Dutch*, *The cold shoulder*, ...
2	*Word contractions formed by just the initials such as ' u ' for ' you '.*
3	*Word contractions with just a part ora syllable of the word, such as ' HAV '.*
4	*Numbers to replace words or syllables of the word as '* 2*hav '.*
5	*Sentences formed by the initials of words.*
6	*Contracted forms of certain English words. Example* : *I' m*, *I' ve*, *I don ' t*, *I ' d.*
7	*Idioms or proverbs to convey certain ideas, principles and values that underlie English culture. Some combinations of words have a figurative meaning and essentially work with images. Example* (*A hot potato*), (*A penny for your thoughts*), (*Add insult to injury*), (*At the drop of a hat*), (*Back to the drawing board*), (*Ballisinyourcourt*) .
8	*Stenographic words consisting of initials, such as* (*u*) *for* (*you*).
9	*Onomatopoeia that reproducing or mimicking the sound of words or phrases to convey certain ideas, good or bad.*

1.4.2 Neural Learning

Neural Learning (NL) is an artificial intelligence technology, enabling computers to learn without be explicitly programmed to it. To learn and increase, however, computers need data to analyze and train on [104]. Abiodun et al. (2018) [104] recommend to focus future research on combining, into one network-wide application, various Neural Networks models.

In Automated Learning, we distinguish regression problems from classification problems. Thus, we consider that the problems of predicting a quantitative variable are problems of regression while the problems of predicting a qualitative variable are problems of classification. Certain methods, such as logistic regression, are both regression methods in the sense of predicting how to belong to each of the classes and classification methods.

Among the existing research studies, a group of studies identifies useful social networking information, using machine learning, to successfully extract structured information from unstructured textual social media contents.

Despite the fact that machine learning is not new concept, many people are still uncertain what it entails. It is a modern science, using data mining, statistics, pattern recognition and predictive analysis for identifying patterns and making data predictions. Towards 1950s, first algorithms were developed. The best known is the Perceptron.

The training data is created from the June 2018 Japan Floods and the October 2010 Haiti earthquake disasters. This information, easily obtained using the neural network, is manually annotated by volunteers.

1.5 Conclusion

With defining and modeling concepts of disasters and disaster management, with proposing disaster classification, exploring and analyzing social media-based disaster management packages in different phases, this thesis aims to explore the social networks potential in managing natural or anthropogenic disasters and shows the impact of social networking paradigm on the improvement of the disaster management process where interactions involving communities are discussed. They have their specific functional needs to act in different phases of the disaster management process. Besides, the communication role means in the attenuation, response and recovery phases is presented. We have explored the potential of P2P networks in managing natural or anthropogenic disasters. The adaptability of P2P networks [58] should be exploited to respond to the characteristics of disaster situations. Although the importance of social networking has already been modeled and reported above, it is also important to empirically validate the potential of social networking in disasters through semi-structured interviews that will be conducted with disaster managers of social media. The choice of these managers will aim to obtain a good combination of cases based on their expertise and areas of operations. Interviews objectives are:

1. Explore the functional needs of disaster managers for action during the mitigation, response and recovery phases.

2. Identify the advantages and disadvantages of using social networking by disaster managers to act during mitigation, response and recovery phases.

In the next chapter, we will introduce the first solution, namely: designing and implementino the neural networks-based alert model.

Research is what I am doing when I do not know what I am doing.

Wernher Von Braun

Chapter 2

Neural Learning-based Automated Learning Environment Retrieving Relevant Content from Social media

Summary

2.1 Introduction

IN recent years, various catastrophic events, summarized in Table 1.1, have occurred. With all these disasters, social media has enabled the population, especially the affected of them, to quickly publish a considerable amount of disaster information to help decision makers make quick and good decisions [44, 80, 105, 106].

With the ability to share a message with a potentially important audience, social networks such as Facebook or Twitter, among others, are used to collect and disseminate relevant and up-to-date information [82], [105]. However, the quantity and quality of information provided during these critical periods and crisis situations can make it difficult to find useful and usable information. Indeed, social networks also serve to sabotage reports such as the Asiana flight accident in July 2013, a photo that is published on Twitter 30 seconds after the accident [3], [107].

Social networks have become a potential resource for communication, detection, monitoring and disaster information extraction to improve the management of natural and anthropogenic disasters [3, 82, 105, 108, 109].

Using social media to communicate timely information in crisis events become a common practice in recent years [109]. Major crises can generate millions of messages on social networks (*eg. 3.5 million messages in one day, during Hurricane Sandy in 2012, and more than 5,500 tweets published every second in the wake of the tsunami and the earthquake in Japan in 2011*) [110]. Manually checking each message and filtering out the relevant ones is a daunting task, if not impossible.

The link between social networks and disaster awareness has attracted increasing attention from researchers with different types of games and simulations for disaster education [3, 83, 98, 111]. These numerous studies have been carried out in recent years for the automatic identification of different types of content on social media [83, 98, 111].

With the proliferation of social networks, an ongoing event is under discussion on all these channels. Affected populations publish useful and timely information of various types, including reports of injuries or deaths, damage to infrastructure or urgent needs on different social networks. This important information obtained in the first hours can be of great help and can also reduce both human losses and economic damage [52, 112]. To get a complete view of the event, it is important to retrieve information from multiple sources. There are generally qualitative differences in the information obtained from different sources. When it comes to retrieve information from social network and alert people to make quick decisions, the task of disaster management is heavy.

The unambiguous nature of Twitter has enabled stakeholders to deliver relevant messages for the crisis and to access vast amounts of information they may not have. However, the Web has several sources of information on which an ongoing event is discussed. Several automated systems have been designed to help disaster managers identify and filter useful information posted on social networking sites [3]. Most of the work has focused on the use of social networks as a source of information on only a few phases of disaster management, including disaster response. However, few are devoted to warning and all methods deal with the retrieval of information from social networks. Generally, Twitter is the main source of information for these systems. The design of disaster management systems with different and diverse sources of information, especially social networks, is a real challenge.

In this work, we propose a new real-time neural network-based alert model for disaster management. It integrates encapsulations from multiple sources. Thus, it retrieves information, combining multiple search results. Thus, we provide, not only, a solution to this challenge, but also, we propose better performances in term of recovery than other similar solutions.

In our proposed solution [15], that is the enhancement of our previous work [14], we try to identify relevant content dealing with impending catastrophic events or just bursting. These disasters can be natural or anthropogenic. Once this information is retrieved (*distinguished, of course, from both large amounts of other content and also abusive information*), it can be used to alert disaster managers to make quick and effective decisions that could help people in need or to save lives. Our main contributions are listed below.

1. We develop a neural-based model that uses low-level content learning capabilities to automatically separate relevant information from redundant (*eg. retweets for Twitter*) or abusive (*eg. community-based*).

2. We develop a neural network-based model that uses content learning capabilities of multiple sources (*ie Twitter and Facebook*) to automatically retrieve relevant information using a set of keywords and hashtags respectively related to various catastrophic events whether natural or anthropogenic.

3. Keeping in mind the limitations of the previous work [14], we develop an event-independent alert model that can be used directly to filter content on multiple source at a time in future events. Experiments on multi-disaster-related tweet flows with diverse characteristics show that our proposed model outperforms vocabulary-based approaches. Our approach filters the content (*Twitter tweets and Facebook messages at a time*).

4. Once we have developed this real-time, neural-based alert model, using multi-source content learning capabilities (*ie Twitter and Facebook*) to automatically retrieve relevant information by using a set of keywords and hashtags respectively, relating to various catastrophic events whether natural or anthropogenic, we tested the proposed model on the two catastrophic events of this end of summer, namely, Japan Floods of June 28 to 09 July 2018 with 2000 dead, 2500 wounded and 330,000 homeless and earthquake of Haiti from 06 October 2018 with 18 dead and 548 wounded.

5. Having identified the relevant information, we have proposed an alert network propagation scheme that permits disaster managers, so they can quickly make effective decisions that would save human lives.

2.2 New Alert Model to Disaster Management

Our approach is the closest to that of Koustav Rudra & al. [80], whom studied Community Tweets (abusive messages). They are targeting specific religious groups,displayed in natural crisises. Except that methods are proposed to counter them, using anti-communal tweets: tweets published by users in crisis events. The advantage of our Automated Learning Environment is that it relies on evidence from all firsthand social media contents (on all the Web).

2.2.1 Information retrieval models from multiple sources

Vulic & al. [98] use comparable document-aligned data to easily learn patterns of common topics or word concepts, in a bilingual recovery. However, the preparation of comparable documented data requires a lot of human involvement and time. Therefore, such approaches are not appropriate when information about an ongoing event should be retrieved quickly. The work of Joseph A. Shaw and Edward A. Fox [99] focuses on methods for recovering separately from different sources and then combining them using data fusion techniques.

Deep learning-based multi-view recovery attempts to learn document embedding in a common space, where no differencing between various data sources [78]. This approach has low performance scores for all used methods: difficult problem and requiring better methods.

According to Cynthia D. Balana [100], Google Crisis Response's (GCR) National Risk Management and Disaster Response Board (NDRRMC) had integrated Facebook and Twitter into its surveillance system and website for a quick response.

In this manuscript, we propose a new alert model for disaster management based on social networks, as [127] and [128]. Our proposed model is based on a semi-supervised inductive technique to use unlabeled, multi-source data, which is often abundant during a crisis event, with less data previously labeled than previous events (*Table 1.2, Table 1.3 and Table 1.4*).

Table 2.1: Comparative table of all techniques and methods used in Alert Models.

Approach	Methods	Identification	OSN	Analysis
[4]	on keywords	Classify messages	Twitter	Real-time
[44]	Statistical analysis	Identifying spatial patterns	Twitter	/
[80]	Annotated data	Identify abusive contents	Twitter	/
[81]	Annotated data	/	Twitter	Real-time
[107]	/	Learning	Twitter	/
[108]	/	Learning	Twitter	/
[109]	Annotated data	/	Twitter	/
[115]	Annotated data	Notification system alerts earthquake	Twitter	/
[118]	Annotated data	CrowdsourcingMachine learning	Twitter	Real-time
[119]	Predefined geographic displays	/	Twitter	Real-time
[120]	on keywords	/	Twitter	/
Our Approach	**keywordsAnnotated messages**	**Learning with NN**	**all the Web**	**Real-time analysis**

2.2.1.1 Foundation of neural learning

Figure 2.1 shows the flow chart showing the functioning, during the first passages, of this alert model to learn the first information that will be manually annotated by volunteers, as shown by Algorithm 1.

Algorithm 1: Learning information using annotated manually contents

1: **begin**
2: **input** (a content$V(w_1, w_2, ..., w_i, ..., w_n)$)
3: **while** ($w_i \in \{Keywords\}$) **do**
4: $\{information\} \leftarrow w_i$
5: skip *to* the *following* content w_{i+1}
6: **endwhile**
7: **output** *listof* information $V(w_1, w_2, ..., w_i, ..., w_n)$
8: **end**

This annotated information is integrated in the model to help the neural network in learning and thus retrieves relevant information that is used in alerting public opinion and disaster managers to make appropriate decisions. Figure 1.2 shows how this alert model works.

Table 2.2: Comparative table of all techniques and methods used in Models for retrieving information from multiple sources including our approach.

Approach	Exigences	Real-Time	Multiple Sources	Method
[78]	Low performance scores	/	/	Multi-view recovery based on deep learning
[98]	Requires a lot of human involvement and time	Not appropriate for real-time approach	/	Learning patterns with comparable documents
[99]	/	/	Recovering separately from different sources	Combining using data fusion techniques
[100]	/	/	$Facebook/Twitter$	/
Our Approach	**Annotating manually information**	**Appropriate for real-time**	**Multiple sources (Facebook Twitter)**	**Learning with Neural Network**

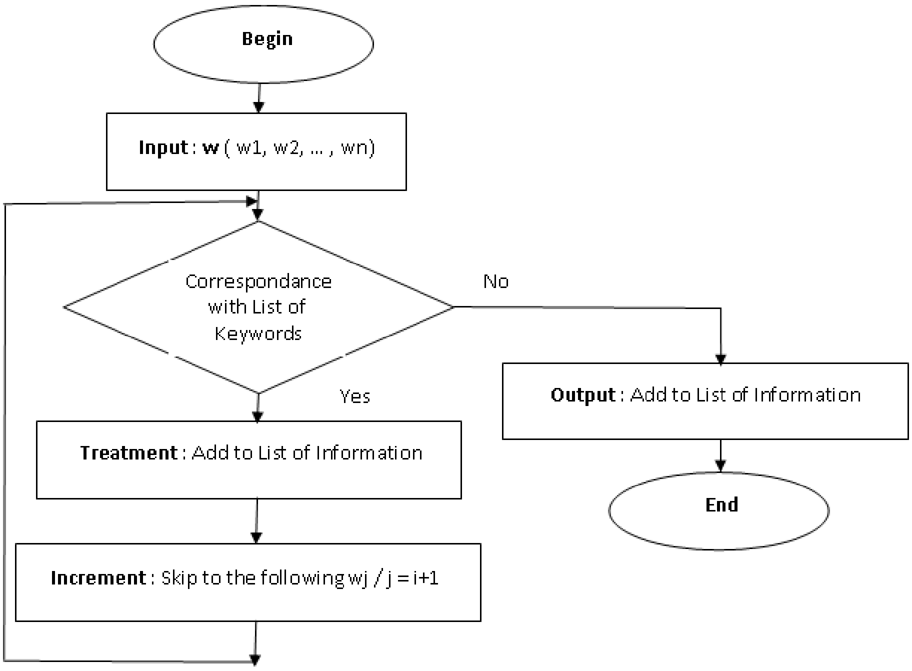

Figure 2.1: Flow chart to determine, using a keywords set, information to be annotated manually for enriching neural network.

Figure 2.1 shows the flow chart showing the functioning, during the following passages, of this alert model to learn the relevant information that will be used to alert public opinion and in particular disaster managers so they can take quick and effective decisions that can save lives, as shown in Algorithm 2.

Configuration of neural learning parameters

We use a neural network with a single hidden layer that takes e_i as input and gives

Table 2.3: Comparative table of all techniques and methods used in Models for retrieving information from multiple sources.

Approach	Exigences	Real-Time	Multiple Sources	Method
[78]	Low performance score	/	/	Multi-view recovery based on deep learning
[98]	Requires a lot of human involvement and time	Not appropriate for real-time approach	/	Learning patterns with comparable documents
[99]	/	/	Recovering separately from different sources	Combining using data fusion techniques
[100]	/	/	Facebook / Twitter	/
Our Approach	**Annotating manually information**	**Appropriate for real-time**	**Multiple sources (Facebook Twitter)**	**Learning with Neural Network**

e_k as output. The input to the network is a content:

$$t = (w_1, ..., w_i, ..., w_n)$$

containing words, coming from a finite vocabulary.

Let :

$$e_i = (w_{i1}, w_{i2}, ..., w_{in}) \ and \ e_i \in C^n, with \ i \in [1, N]$$

containing words each coming from each a finite vocabulary V, the incorporation of a content of the source message i relevant for, at least, a keyword :

$$H_j \in \mathbf{H} \quad with \ j \in [1, M].$$

We want the learning of a generic space with the neural network, as:

$$\mathbf{E} = \{e_k; \quad k \in [1, K]\}$$

which normalizes the differences:

$$E = [\mathbf{E} - \mathbf{RDF}]$$

where :

$$\mathbf{RDF} = [\mathbf{R} + \mathbf{D} + \mathbf{F}]$$

Through the neural network, the transformation of e_i into e_k can be explained by:

$$e_i \rightarrow e_k = \{e_i; \quad such\ as\ e_i\ is\ relevant\ for\ H_j\ and\ w_i;$$

$$H_j \in \mathbf{H} \quad with\ j \in [1, M]\}$$

where

$$w_l \in \mathbf{W}; \quad with\ l \in [1, L]; \quad e_i \in [\mathbf{R} + \mathbf{D} + \mathbf{F}];$$

$$with\ k \in [1, K]; \quad i \in [1, N]$$

D, **R** and **F** represent respectively the set of duplicate re-tweets, duplicate contents and false alerts. The objective is then to maximize the size K of the set E. Figure 2.3 shows the Artificial Neural Network Architecture.

Algorithm 2: Determining relevant information with annotated information.

begin
    input (a content$V(w_1, w_2, ..., w_i, ..., w_n)$)
    while ($w_i \in \{Keywords\}$) **do**
        $\{information\} \leftarrow w_i$
        skip to the $following$ content w_{i+1}
    endwhile
    output $list$ of $information$ to be annotated
    while ($w_i \in \{information$ annotated $manually\}$) **do**
        $\{information\} \leftarrow w_i$
        skip to the $following$ content w_{i+1}
    endwhile
    output $listof$ information $V(w_1, w_2, ..., w_i, ..., w_n)$
end

De Albuquerque & al. [52] used only statistical analysis to identify general spatial patterns in flood-related tweets, associated with floods proximity and severity. While Robinson & al. [125] presented a notification system for identifying earthquakes, but also, in first-hand reports published on Twitter from tweets of target areas in Australia and New Zealand.

Besides, with the reinforcement of using microblogging platforms as Twitter in sudden natural or anthropogenic disaster, thousands of disaster-related messages posted. These online messages contain important information, useful if dealing quickly and effectively, to make quick decisions for helping affected community [11, 39]. Many types

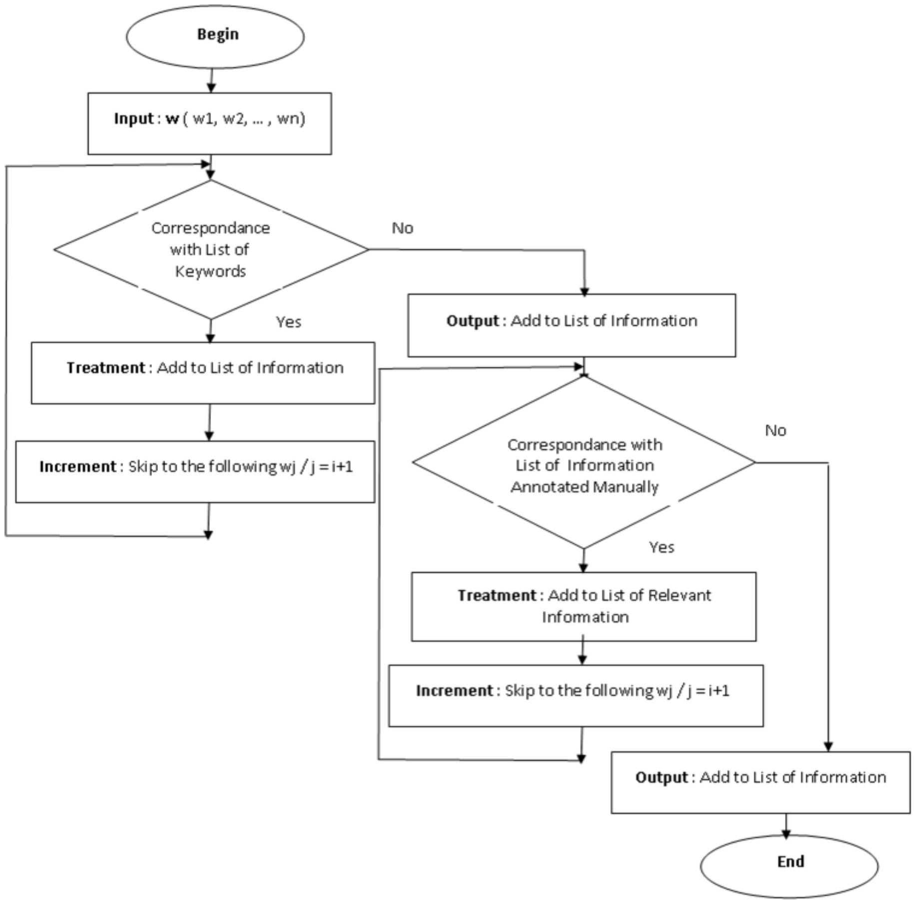

Figure 2.2: Flow chart for determining relevant information using a set of manually annotated information

of processing techniques ranging from machine learning to natural language processing through computational linguistics have been developed [58] for different purposes [64]. However, fully exploiting this data, despite the existence of some resources, such as annotated data and standardized lexical resources [121, 122]. Terpstra & al. [129] present a real-time analysis of Twitter data. Besides, they use predefined geographic displays, Twitter content, etc, to filter and analyze crisis information.

Most event detection methods are based on keywords [59], such as Imran & al. [123], which analyze keywords used in tweets during catastrophic events to classify messages as real-time event reports, using a support vector machine (SVM). This related research includes the methodology of Vieweg & al. [124] and disaster ontology to identify also tweets that provide only situational awareness. Kongthon & al. [40] develop classifiers for analyzing only the floods tweets in Thailand in 2011. Besides, Starbird & al. [22] and Vieweg & al. [29] analyzed the use of microblog and disasters life cycle [123].

Bella Robinson & al. [125] developed a notification system alerting about earthquakes, from only first-hand reports published on Twitter. João Porto de Albuquerque & al. [52] examined Twitter platform microblogging (*tweets*) produced during the Elbe flood in June 2013 in Germany, using only, statistical analysis to identify general spatial patterns in flood-related tweets, associated with floods proximity and severity.

Our approach is most closely related to that of Koustav Rudra & al. [80], who studied Community Tweets, that are, abusive messages targeting specific religious / racial groups displayed during natural disasters. Except that methods are proposed to counter them, using anti-communal tweets, published by users in crisis events.

Table 2.4: Comparative table of all techniques and methods used in Alert Models

Approaches	Methods	Identification	Used OSN	Real-time analysis
[11]	/	Learning	Twitter	/
[52]	Statistical analysis	Identifying spatial patterns	Twitter	/
[59]	Based on keywords	/	Twitter	/
[121]	Annotated data	Hybrid crowdsourcing Machine learning	Twitter	Real-time
[122]	/	Learning	Twitter	/
[123]	Based on keywords	Classifying messages	Twitter	Real-time
[125]	Annotated data	A Notification system alerting earthquakes	Twitter	/
[80]	Annotated data	Identifying Community Tweets (abusive messages)	(Tweets) Twitter	/
[129]	Predefined geographic displays	/	Twitter	Real-time
[130]	Annotated data	/	Twitter	/

2.2.1.2 Functioning of neural learning

Figure 2.1 shows the architecture of the neural network that functions according to all the functionalities presented in Figure 2.2.

Table 2.5: Classification of Neural Learning architectures.

Type	Architecture	Model - Training - Algorithm - Application	Ref
NL	Neural Network / Machine Learning	Discriminative-Supervised-Gradient Descent based Backpropagation-Classification	[14, 15]

Perceptron is a supervised learning algorithm for binary classifiers, that is a function to decide if an input (numbers vector) belongs to specific class. It makes predictions

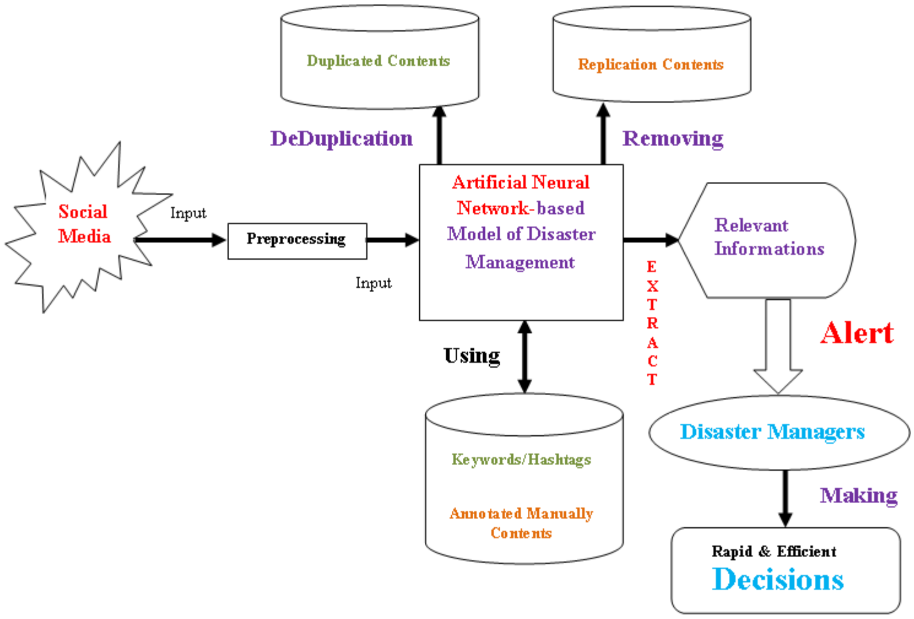

Figure 2.3: Neural Network-based Alert Model Architecture.

thanks to a linear predictor function, combining a weights set with the feature vector. Figure 3.5 shows the Neural Network-based Alert Model.

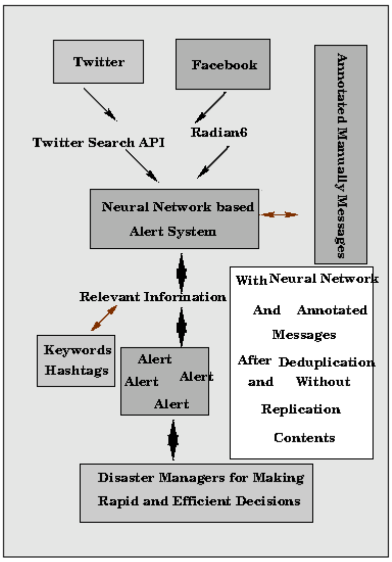

Figure 2.4: Neural Network-based Alert Model

Whether it's Twitter, Facebook or other social networks, these are platforms where people often express emotions. We detected emotions, using four characteristics types, namely : emoticons, blasphemy, interjections and general message feeling [128]. Emoticons, blasphemies and interjections are widely used to convey emotions such as happiness, surprise or anger. For identifying these features types, we used a tags combination in the tagger (*containing tags for interjections, emoticons, etc.*), compiled interjections and blasphemies lists on the Web for French, Spanish and English, and regular expression patterns for emoticons [131].

Messages from Indonesia's target regions are checked for frequency bursts of disaster keywords and processed to identify evidence of a disaster. The advantage of our Disaster Alert model is that it relies on evidence from Twitter's and Facebook's first-hand reports. An input document vector, is associated by this template, with a neural network-based multi-view space, whose contextual information is available.

2.2.2 Network Propagation Scheme

Having identified the relevant information, we have proposed different ways to alert public opinion but especially disaster managers so that they can quickly make effective decisions that can save lives. Figure 1.4 shows the flow chart of the network propagation scheme of the alert.

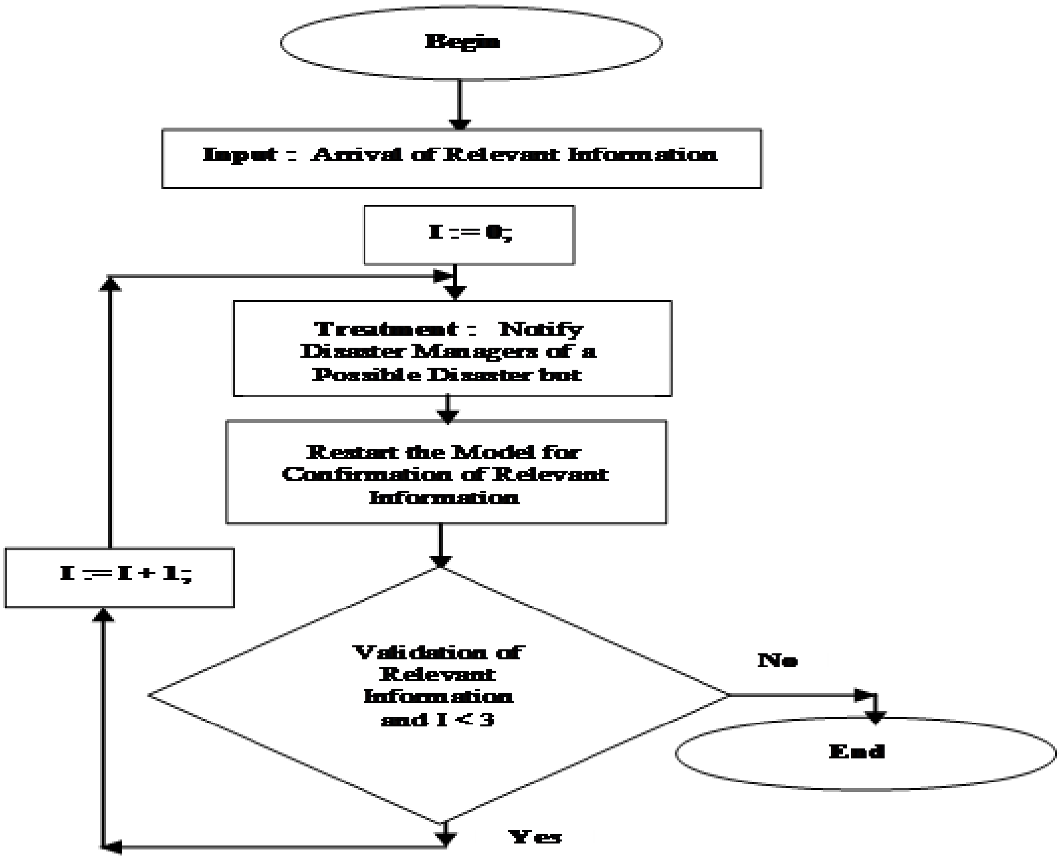

Figure 2.5: Flow chart of the network propagation scheme of the alert.

2.2.3 Performance Evaluation

We took into account the contents posted during catastrophic events summarized in Table 1.1. Note that the events (1), (2), (3), (4), (5), (6), (7) , (11), (12) and (13) are natural disasters and events (8), (9), (10) and (14) are anthropogenic disasters. In addition, we took into account events occurring in different geographic areas so that this document is not influenced by any type of demographic data. The contents will be available to the community of potential researchers. We applied end-to-end key matching (API) search in Twitter and Facebook at each event according to [78]. For example, for the contents related to the event (2) of the earthquake of Haiti of January 12, 2010, we are looking for content with keywords such as *earthquake*, *Haiti*, Haiti earthquake for the messages of Facebook and #HaitiEarthquake, #Haiti and #Earthquake, for tweets from Twitter. For each word, we collected all the tweets returned by Twitter. We only consider contents in English for Facebook or Twitter. For each event, we report the number of content (*tweets and messages*) In order to show the effectiveness of our proposed model, we examined a specific event - the Indonesia earthquake in September 28th, 2018 and the Japan flood in July 2018 - and post-event contents on two social media: Facebook and Twitter.
The tweets were collected using the Twitter Search API using the #indonesia and #earthquake hashtags for the September 28, 2018 earthquake in Indonesia and the #Japan and #floods hashtags for floods. July 2018 in Japan. Facebook posts have been collected using the Radian6 tool in real time, as it allows. Facebook content was obtained using the search terms *Indonesia* and *earthquake* for the 2018 Indonesia earthquake and the *Japan* and *flood* keywords for the 2018 Japan floods.

With the neural network and after de-duplication, we have obtained the results illustrated on Table 2.6. All experiments reported here were performed on these two sets of data.

Table 2.6: Examples of Contents Obtained, for a Set of Keywords or Hashtags, After De-Duplication.

Annotated	**Indonesia**	**earthquake**	**Japan**	**floods**
Contents	Twitter (Tweets)	Facebook (Contents)	Twitter (Tweets)	Facebook (Contents)
Contents	$51,109$	$76,338$	$36,077$	$12,325$

Standard relevance queries and judgments: we identified a set of disaster-specific information needs, as proposed in [52]. It's a set of keywords and hashtags for Facebook and Twitter respectively. Data collection and filtering are at the heart of disaster management using social media. The algorithms used to warn and alert depend on the messages published on the social media and their quality. Thus, every effort must be made to maximize the number of messages relevant to the disaster and to remove non-informative messages as proposed in [132]. These contents are manually tagged to remove those (*non-informative messages*).

To understand the models and evaluate our proposed model for extracting relevant information through semantically-based learning, we need an annotation for a set of contents. We randomly sampled 1366 messages (*with 547 Facebook content and 819 tweets*) after deleting the duplicates, as reported in table2.6. These messages were observed independently by ourselves. The goal was to identify all relevant content relatively to the predefined keywords. Table 2.7 presents the relevant documents number found for each hashtag or keyword from two datasets.

Table 2.7: Examples of Relevant Content for a Set of Keywords or Hashtags.

Annotated Contents	**Indonesia**	**earthquake**	**Japan**	**Floods**
	Twitter (Tweets)	Facebook (Contents)	Twitter (Tweets)	Facebook (Contents)
Anthropogenic Disaster	55	59	18	32
Natural Disaster	289	192	255	268

Content, obtained in this table, manually annotated and cleaned from non-informative messages, will be used, in this neural network-based space, to analyze live new messages.

As we want our alert model to be event - independent, it must be able to be used directly on content posted at later events. Besides, we adopt the approach of using a features set for content extraction task. As we have a wide number of data sets (*14 sets of data*), a few is dedicated to training and others to check proposed model performance.

We compare the performance of the proposed set of features in two scenarios:

1. Classification in the field : where the classifier is trained and tested with content related to the same event using cross-validation and
2. Classification inter-domains : where the classifier is trained in the contents of an event and tested in another event. In this case, all the annotated contents of a particular event are used to form / develop the model, and then it is tested on all the contents of the rest of the events.

2.2.3.1 Model Selection

The performance of this system strongly depends on the selection of the appropriate model. We are now trying to select the most appropriate model for our proposed feature set based on specific criteria.We consider four advanced classification models for the feature set above:

1. Random Forest (RF);
2. Logistic Regression (LR);
3. Naive Bayes (NB) and
4. Rule Based Classifier (RBC)

We follow a simple approach - if any of the features mentioned above are present in a content, we mark it as relevant. Our neural network-based alert model is applied to all these pre-prepared data models. To judge the performance of these data models on the feature sets mentioned above, we have defined the following evaluation criteria. Each criterion is calculated and averaged over the different sets of training data.

1. Average accuracy in the domain: average accuracy of our alert model for the different events of the learning set, as in the scenario in the domain.

2. Medium inter-domain accuracy: average accuracy of our alert model in different inter-domain scenarios among the different events in the learning set.

3. Average accuracy for content: the detection of content with high accuracy is a necessary condition for our alert model. Therefore, we consider the average accuracy in training datasets.

4. Average F score for the contents: F, the system score, indicates the balance between precision, accuracy, recall and coverage.

Table 2.8 shows the Score Assessment Parameters for Ranking Models Using the Proposed Characteristics of the results shown in table 2.7.

Table 2.8: Score Assessment Parameters for Ranking Models Using the Proposed Characteristics.

Classifier	**Precision in the Domain**	**Inter-Domain Precision**	**Precision**	**F-score**
Random Forest	0.9042	0.9304	0.9324	0.9258
Logic Regression	0.9135	0.8919	0.9113	0.8941
Random Forest	0.9254	0.9117	0.9509	0.9112
Random Forest	**0.9308**	**0.9307**	**0.9518**	**0.9291**

2.3 Conclusion

This chapter represents the first attempt to extract, in real time, information on catastrophic events from multiple sources on the Web (*Facebook and Twitter*) and to immediately alert disaster managers so that they can make quick and effective decisions that could, perhaps, save lives. Indeed, we propose a new ad hoc real-time alert model for the management of disaster, whether natural or anthropogenic, based on a new multi-view recovery model from multiple sources. This approach is useful for local monitoring, in general, as well as for any local event monitoring to help making appropriate decisions.

1. We have developed a neuron-based model that uses low-level content learning capabilities to automatically separate relevant information from redundant (*eg. retweets for Twitter*) or abusive information (*at the level of the community, for example*).

2. This model, based on a neural network, uses the learning capabilities of multiple source content (*here Twitter and Facebook*) to automatically retrieve relevant information using a set of keywords and hashtags respectively, related to various catastrophic events, whether natural or anthropogenic.

3. Keeping in mind the limitations of the previous work [14], we have developed an event-independent alert model that can be used directly to filter content from multiple sources at future events. Experiments on multi-disaster-related content flows with diverse characteristics show that our proposed model outperforms vocabulary-based approaches. While our approach filters content (*Twitter tweets and Facebook posts at once*).

4. Once we developed this real-time alert model, we immediately tested it on the two catastrophic events of late summer, namely the Japan Floods from June 28 to July 9, 2018 with 2,000 dead, 2,500 wounded and 330,000 homeless and the earthquake of Haiti of October 6, 2018 with 18 dead and 548 wounded.

5. We have also proposed a warning network propagation scheme that will enable disaster managers to make effective decisions quickly and effectively to save lives.

In the next chapter, we will introduce the first enhancing of the alert model, namely: designing and implementing the Deep Learning-based Automated Learning Environment (ALE).

There is something fascinating about science. One gets such wholesale returns of conjecture out of such a trifling investment of fact.

Mark Twain

Chapter 3

Deep Learning-based Automated Learning Environment through Social Media for Disaster Management

Summary

3.1 Introduction

IN recent years, the frequency of large-scale disasters has increased worldwide. Boumerdes earthquake [1] of May 21, 2003 and Chlef earthquake (Algeria), occurred in 1980 (7.3 degrees on the Richter scale), caused 2,633 dead and collapse of 20,000 homes. Whenever a crisis strikes, many recognize importance of managing disaster. The majority of disasters have huge and lasting impacts on human lives and societies. For minimizing consequences of such events, it is advised to prepare and develop resilient communities thanks to educating them with appropriate and up-to-date information necessary to cope with crisises. We examine how to develop competences in response to unplanned event, whether in preparation, in disaster management or in the institutional aspect.

Our analytical framework is guided by the important social phenomenon occurring in any every disaster with the vastness of activity surrounding this catastrophe with all these volunteers ready to help people in need by all means. Disasters, as tsunamis, terrorist acts, explosions, floods and earthquakes result in human suffering, loss of property and other negative consequences [2].

Using social networking enables to post situational updates in various forms as videos, images and text messages. Numerous studies [3] show online information usefulness for a quick response for managing disaster. These analyzes of using social networks in disasters have identified a distinct role for local users of the event, whom are likely to generate useful information to improve situational awareness [4].

Thanks to the storage technics improvement (big data) and the use ease, the participatory culture and the end-users interoperability (Web 2.0), we are confronted with information overload stored, notably the Web, a popular and interactive way of disseminating information today. It is notably immense, diverse and dynamic. This new era is defined by the knowledge rapid development and traditional learning inability to cope with growing complexity and rapid changes of the new knowledge society. Therefore, a new vision of learning is needed, namely Automated Learning, aiming to discover, in large amounts of data, valuable information that can help understand them or predict the behavior of future data. This process involves examining wide data amounts (stored in warehouses or in streaming) using statistical, mathematical and eventually AI techniques. This knowledge, initially unknown, is either a correlation, pattern or general trends in these data. Automated Learning is based on analyzing problems to understand their principles and thus develop, for them, mathematical models. Besides, experimental data are required to verify the system correction or some difficult parameters estimation to model mathematically [5]. A fundamental shift, towards a more open learning model and centered on learner, is needed where Automated Learning uses various manual and automatic tools: starting by describing the data, summarizing their statistical attributes (means, variances, covariance), visualizing them using the curves, the graphs, the diagrams, and finally looking for the significant links potential between variables (repeated values). Data description alone does not provide a action plan. We must build a prediction model based on discovered information, and validate it on other data. Recently, it was argued that Automated Learning could find answers to the needs of the new knowledge society and so transform learning. However, in many cases, systems are too complex to model them mathematically. Automated Learning, suggesting complex and unimaginable specific impacts on the society and more widely the economy, remains primarily in computer science, while being closely linked to cognitive science, neuroscience, biology and psychology, and able to lead to crossroad of systems, nanotechnology, biotechnology and cognitive science, thus leading to artificial intelligence with a wider base.

Smart Disaster education enables community members to develop managing crisis skills. Besides, these members share their knowledge and help one another in preparedness, like Evacuation drills, Games Based-Evacuation Drill [6], Paradigmatic Tourism [133], Dark Tourism, Penumbral Tourism, Mixed Realistic Games or Alternative Realistic Games (ARG) [8] and tower defense game [9], or other evacuation techniques as Simulations.

In this work, we present the theoretical, design, implementation and evaluation details of our environment [16], a learning framework. Its main objective is helping users become familiar with all different learning models thanks to a wide variety of digital available data. This automated learning environment is fundamentally ubiquitous, distributed, flexible, dynamic, social and personal.

3.2 Deep Learning-based Automated Learning Environment via Social Media to Enhance Disaster Management with Disaster Education

This section includes the study of automated learning, disaster and disaster management, social networking and education.

3.2.1 Improving Automated Learning

Artificial intelligence (AI) combines reinforcement learning (RL) and deep learning (DL) [104]. It is represented mathematically, as(see Figure 2):

$$AI = RL + DL \tag{3.1}$$

where: AI represents Artificial Intelligence, RL represents Reinforcement Learning, and DL represents Deep Learning.

3.2.2 Machine learning (NN)

Machine Learning is an artificial intelligence technology, enabling computers for learning without be explicitly programmed. Learning and modeling need data to analyze and train on.

Besides, machine learning is not new. Still confused, it is a modern science to discover patterns and predict, from data, thanks to predictive analysis, pattern recognition, data mining and statistics. First algorithms were created in the 1950s. *Perceptron* is the best known of them..

The perceptron is an algorithm for binary classifiers, using supervised learning. A binary classifier is a function deciding if an input (as vector of numbers) belongs to a specific class. Linear classifier makes predictions thanks to a linear predictor function combining a weights set with the feature vector. The perceptron algorithm was invented in 1958 [134], funded by the United States Office of Naval Research.[14, 15]

3.2.3 Deep learning

In recent years, Deep learning methodologies have achieved impressive results in computer vision [135], speech recognition, image processing, and handwritten recognition of characters, while they is currently in its infancy in fault diagnosis [136]. It can also overcome limitations of shallow networks that prevent efficient training and abstractions of hierarchical representations of multi-dimensional training data [136] in many instances. Deep learning offers a set of units such as [137] convolution unit, [138] recurrent unit, and long-short term memory unit for feature extraction on samples with distinct features, delving into the math behind training algorithms used in recent deep networks, explaining existing shortcomings, [136] improvements and implementations. The paper also covers different types of deep architectures corresponding to the two types of learning such as Feedworward and Feedbackward neural networks.

3.2.3.1 Classification of Deep Learning Models

Feedforward neural networks are not capable of extrapolation [139]. Disavantages of ResNets are Increased complexity of architecture such as Implementation of Batch normalization layers since ResNet heavily depends on it and Adding skip level connections for which the dimensionality is essential between the different layers.

Table 3.1: Classification of Feedforward Neural Network (FFNN) architectures with Model, Training, Algorithm, Objective and Limitations.

Architecture	Model - Training - Algorithm - Application	Limitations	Ref
FFNN	Supervised-Gradient Descent based Backpropagation-*Binary classification*	No Extrapolation [139]	[16, 17, 140]
ConvNets (CNN)	Discriminative-Supervised-Gradient Descent based Backpropagation- *reducing frequency variations; Image recognition / classification*	Temporal modeling-No increasing validation precision with layers stacking-not encoding objects position and orientation [143, 144]	[18, 47, 141, 142]
ResNets	Discriminative-Supervised-Gradient Descent based Backpropagation-*Image recognition*	Increased complexity of architecture; Implementing Batch; Adding skip level connections	[16, 17, 140]
Auto-encoder	Generative-Unsupervised-Backpropagation-*Image recognition*	not discover slow modes [148]	[138, 145, 146]
Generative Adversarial Networks	Generative-Discriminative-Unsupervised-Backpropagation-*Generating realistic fake data-building 3D models or image improvement*	distribution learning poorly made[1]	[28]
Restricted Boltzmann Machine (RBM)	supervised or unsupervised-Generative with Discriminative finetuning-Unsupervised-Gradient Descent based Contrastive divergence-*Dimensionality reduction, feature learning, topic modeling, classification, collaborative filtering, body quantum mechanics*	difficult training; tricky partition function making computing log likelihood infeasible	[138]
Recurrent NN (RNN)	Discriminative-Supervised-Gradient Descent & Backpropagation through Time-*Natural Language Processing; Language Translation; Sequences recognition*	Difficult inference, of time series unsupervised problem, in negative time [147]	[138, 145, 146]
Bi-directional RNN	Discriminative-Supervised-Gradient Descent & Backpropagation through Time-*Natural language processing (NLP)*	Trained with limitation of input information [147]	[28]

Table 3.2: Classification of Deep Learning architectures with Model, Training, Algorithm, Objective and Limitations.

Type	Architecture	Model - Training - Algorithm - Application	Limitations	Ref
FBNN	LSTM	Discriminative-Supervised-Gradient Descent & Backpropagation through Time- *Natural Language Processing; Language Translation; Temporal data as stock market*	No obtaining well-defined temporal information [144, 149]	[138]
	Fully Connected-LSTM	Discriminative-Supervised-Gradient Descent & Backpropagation through Time-*Natural Language Processing; Language Translation; temporal modeling; Learning non-linear and complex processes*	No obtaining well-defined temporal information [144, 149]	[150]
	Bi-Directional LSTM	Discriminative-Supervised-Gradient Descent & Backpropagation-*Time-natural language processing and language translation*	Bad Presentation with multi-level features [143]	[141]
Radial Basis Fct NN	RBF Network	Discriminative-Supervised and Unsupervised-*M-means clustering, Least square function, function approximation-time series prediction*	slow classification due to computing RBF function	[151]
Kohonen SO NN	Nodes arranged in grid	Generative-Unsupervised-*Dimensionality reduction, optimization problems or clustering analysis; Competitive Learning*	SOM algorithm Problems[2]	[151]

Resnets, a CNN variant designed for Computer Vision image classification tasks, introduced for skiping connections, was proposed to overcome the VGG styled CNNs problems, as no guarantee an increase in validation accuracy, with stacking convolutional (CNNs) layers does (to make the model deeper). While, after increasing the number of such ConvNets layers for a certain limit, the generalization ability and validation accuracy decrease. CNN does not encode object position and orientation and cannot be spatially invariant to the input data.

The autoencoder, based on deep learning regression, can discover slow modes in dynamic systems. However, a rigorous analysis of nonlinear autoencoders remains lacking. Autoencoders can not correctly discover slow modes and fail [148].

The distribution Psynth produced by the generator is on a small number of images, quite far from those on real images, and yet the discriminator cannot meaningfully distinguish between the two distributions.

GANs, with finite-size discriminators and generators, do not learn distribution very well, even with the successful onset of learning.

Restricted Boltzmann Machine (RBM) is applied algorithm used for collaborative filtering, regression, classification, topic modeling, and feature learning. Used widely in many large scale industries, RBM deals with basic composition unit, progressively grown into many popular architectures. Restricted Boltzmann machine is used for Sparse image reconstruction in mine planning, neuroimaging, as well as in Radar target recognition.

RBM can solve imbalanced data problem, using SMOTE procedure. It find missing values by Gibb's sampling, applied to cover unknown values, overcoming the noisy problem labels by uncorrected label data and reconstruction errors. Unstructured data problem is rectified by feature extractor, transforming the raw data into hidden units.

3.2.3.2 Discussion about Deep Learning Models

The primary disadvantage is the difficulty to train well since the common algorithm used (Contrastive Divergence) requiring sampling from a Chain of Monte Carlo Markov: it requires care to get things just right.

We can at least, in an autoencoder, track cross entropy, being minimized by the model of learning algorithm-back (propagation of errors). The generator produces a distribution Psynth supported on a small number of images, quite far from the distribution on real images, and no meaningfully distinguish between the two distributions.

When a deeper feedforward neural network is created, it can be giving the model the ability to capture more complex representations, as for Image recognition tasks (CNN), Natural language processing (as work of Google Translate), Bio-informatics tasks (as figuring out gene relationships) or Voice recognition tasks.

If it is tried to create a deep neural network to model more simpler phenomena, it is running the risk of over-fitting the data, losing the ability able to generalize to new examples and factoring the amount of resources ti takes to train a deep neural net. When training deep neural networks it often have to use specialized hardware (i.e. a dedicated GPU) or cloud computing services (i.e. AWS, Google Cloud) to train the network effectively.

Two important variations for LSTM model are deep LSTM (DeepLSTM) and convolutional LSTM (ConvLSTM). DeepLSTM differs in the layers number in the model. A single-layer LSTM cannot obtain well-defined temporal information. However, when many layers are stacked in the model, it will be able to acquire better temporal features and so be most suitable to capture motion in the temporal dimension. In ConvLSTM, data are first passed through convolutional layers, ensuring in capturing spatial features. The output from the CNN is provided to the LSTM to get temporal features. Thus, the model will capture a motion relatively to both space and time. These two variants can also be combined to give a Deep ConvLSTM (Deep ConvLSTM), where the outputs of a CNN are passed to a multi-layered stacked LSTM, ensuring better results at the cost of increased computational complexity [149].

Comparatively to RNN, the BRNN can be trained with no limitation of using input information just up to a preset future frame. As an unsupervised task example, gaps filling in high-dimensional time series with complex dynamics, where unidirectional RNNs were recently trained successfully to model time series, but, in the negative time direction, inference is non-trivial [147]. Both CNNs and LSTM have shown improvements over Deep Neural Networks (DNNs) in a wide speech recognition tasks variety. DNN, CNN and LSTM are complementary in their modeling capabilities, as:

- CNNs are best at reducing frequency variations,
- LSTMs are best at temporal modeling, and
- DNNs are best for mapping features to a more separable space.

It is interesting to take advantage of the complementarity of DNNs, CNNs and LSTMs by combining them into one unified architecture [144].

ConvNets present some limitations of temporal modeling [143]. The Bi-directional Long Short-Term Memory (BLTSM) conventional models have some limitations with multi-level features. They can keep track of the temporal information while enabling deep representations [143].

In DBLSTM (Deep Bi-directional LSTM) architecture with multi-levels feature for classifying sentiment polarity on social data, it was able to exploit more level features and modeling inheritance temporal than BLTSM [143].

The advantages of RBF (Radial Basis Function Networks) are simple modeling, good generalizing, big tolerance to input noise, and big online learning capabilities.

Although the training is faster in RBF network, classification is slow relatively to Multi-layer Perceptron: due every node in hidden layer have to compute RBF function for input sample vector, in clssification.

Kohonen Self Organizing NN is very popular thanks to its algorithm easy to understand, its simplity to use and its good and intuitive results.

3.2.3.3 Abiodun Recommendation

They are inherent to the model of mapping data points from a space of high dimensional data onto a 2-dimensional map, while respecting local distance. It can be overcome by using Somor Gtm combined with other data-mining methods such as pure clustering or multi-dimensional scaling techniques.

Abiodun et al. (2018) [104] recommend that future research can focus on combining various NN models into a single network-wide application, as needed and depending on the various NN models features.

3.2.3.4 Deep Learning Architectures

Table 3.3: Classification of Social Media-based Recent Neural Learning Approches of Disaster Management.

Social Media-based Approches	References
Twitter	[28, 141, 47]
Twitter & Facebook	[14, 15]
All the Web	[16, 17]

Neural learning is carried out by Feedforward (FFNN) or Feedback neural network (FBNN). In Feedforward neural network, we have supervised learning such as Feedforward neural network itself for classification [16], convolutional neural network [18, 47, 141] for image recognition/classification or Residual neural network (ResNets) [152] for image recognition, and unsupervised learning such as Autoencoder [138] for Dimensionality reduction and encoding, Generative Adversarial Network [28] network to generation of realistic false data, reconstruction of 3D models or enhancement of images and with supervised or unsupervised learning as Restricted Boltzmann Machine [138] for dimensionality reduction, feature learning, topic modeling, classification, collaborative filtering or many body quantum mechanics.

In Feedback neural network (FBNN), we have supervised leaning as Recurrent neural network [138] for sequences recognition as precise timing, Bidirectional Recurrent Neural Network [28] for natural language processing (NLP), Long Short-Term Memory [138] for temporal data as stock market values over a period of time, video frames, Fully Connected-LSTM [150] for learning non-linear and complex processes in hydrological or meteorological modeling and Bi-Directional-LSTM [141] through time-natural language processing and language translation.

Neural learning can be trained in a supervised / unsupervised manner by Radial Basic Function Network [151] for M-means clustering, least squares function, function approximation and time series prediction or so not supervised by Kohonen Self Organizing Netowork [151] for dimensionality reduction, optimization problems or clustering analysis.

3.2.4 Improving Social Networking

Social Network plays an important role in managing disaster. Collecting and classifying the content (information and images) posted on social networks platforms, for helping humanitarian organizations to be aware of the situation and launching relief operations, understanding voluminous and high velocity data is a task more difficult, requiring the following Crowdsourcing, Crowdtasking and Collaborative crisis Management.

- **Collaborative Disaster Management**

  Crisis is a situation that requiring quick and effective collaborative decisions, with a high degree of uncertainty and complexity [153].

- **Crowd-sourcing and Crowd-tasking in Disaster Management**

  Crowd-tasking describes the managing volunteers, by applying new media and the Crowd-Tasking System (CTS) is defined as combining technical solutions (crowdtasking applications), task managers and task management software in the situation room with volunteers [19].

The rise of social networks has enabled ad hoc citizen groups to organize useful large-scale activities, and in a flexible way. In post-disaster relief operations, it is assumed that all fixed cellular infrastructures do not be functional. The adaptability of Peer-to-Peer (P2P) networks must be exploited to respond to the characteristics of disaster situations. P2P networks have been used to interconnect field workers by just one active connection between a peer and the control room to perpetuate the disaster management system. Thus, the benefits of applying the P2P paradigm have applied to the Geo-Collaboration for Disaster Management as an alternative to the most common Client/Server approaches of GIS and propose to interconnect mobile operators through P2P networks. Mobile P2P systems are a relatively new approach to combine P2P concepts with technologies of mobile computing as Bluetooth, Wireless LAN and telecommunication networks such as GSM, GPRS or UMTS Mobility support is becoming an increasingly important research topic in the design of P2P systems, especially in Disaster Management. Thus, flexibility and independence of users can also be increased physically, to interact with P2P-based mobile anytime, anywhere mostly in Disaster Management. Study found new trends in research in managing crisis focus on two wide trends, namely [154] Prediction and monitoring for early warning, retrieval of relevant information and classifying situation awareness.

Models for retrieving information from multiple sources

In a bilingual recovery, comparable document-aligned data [98] is used to easily learn patterns of common topics or word concepts. However, the preparation of comparable documented data requires a lot of human involvement and time. Therefore, such approaches are not appropriate when information about an ongoing event should be retrieved quickly. The work of Joseph A. Shaw and Edward A. Fox [99] focuses on methods for recovering separately from different sources and then combining them using data fusion techniques. Deep learning-based multi-view recovery, attempting to learn document embedding in a space, with no difference between various data sources. Unfortunately, this approach has low performance scores for all methods used, which indicates that the problem is difficult and a better method is needed. According to Cynthia D. Balana [100], Google Crisis Response's (GCR) National Risk Management and Disaster Response Board (NDRRMC) had integrated Facebook and Twitter into its surveillance system and website for a quick response.

Table 3.4: Comparative table of all techniques and methods used in Models for retrieving information from multiple sources.

Approach	Exigences	Real-Time	Multiple Sources	Method
[78]	Low performance scores	/	/	Multi-view recovery based on deep learning
[98]	Requires a lot of human involvement and time	Not appropriate for real-time approach	/	Learning patterns with comparable documents
[99]	/	/	Recovering separately from different sources	Combining using data fusion techniques
[100]	/	/	Surveillance System Facebook and Twitter	/
Proposed Approach	**Annotating manually information**	**Appropriate for real-time**	**Multiple sources (Facebook Twitter)**	**Learning with Neural Network**

Whether it's Twitter, Facebook, Viber, Messenger, any forum or any thing in the Web, these are platforms where people often express emotions. Emotions are detected using four types of features, namely: interjections, blasphemy, emoticons, and the general feeling of the message.

Emoticons, blasphemies and Interjections are widely used to convey emotions such as anger, surprise, happiness, etc. To identify these features types, a combination of POS tags is used in the tagger, compiled lists of blasphemies and interjections on the Web and regular expression patterns for emoticons.

Table 3.5 shows a comparison of all techniques and methods used in Online Listening and/or Monitoring.

Table 3.5: Comparative table of all techniques and methods used in Online Listening and/or Monitoring.

Approach	Tool	Methodology	Used OSN
[78]	Twitter APIs for tweets and Radian6 for Facebook messages	on the basis of keywords, annotated manually messages, harvesting and cleaning contents and extracting relevant information	Twitter & Facebook
[14]: our previous work	**Twitter APIs for tweets and Radian6 for Facebook messages**	**Based on keywords, Annotated manually messages, harvesting, cleaning contents and Learning Relevant information with neural network, in <u>Real-time</u>**	**Twitter & Facebook**
Proposed Approach	**Radian6 for all contents**	**Based on keywords, Annotated manually messages, harvesting, cleaning contents and Learning Relevant information with neural network, in <u>Real-time</u>**	

Our proposed model is based on a semi-supervised inductive technique to use unlabeled, multi-source data, which is often abundant during a crisis event, with less data previously labeled than previous events (*Table 2 and Table 4*).

Table 3.6: Comparative table of all techniques and methods used in Models for retrieving information from multiple sources.

Approach	Exigences	Real-Time	Multiple Sources	Method
[78]	Low performance scores	/	/	Multi-view recovery based on deep learning
[98]	Requires a lot of human involvement and time	Not appropriate for real-time approach	/	Learning patterns with comparable documents
[99]	/	/	Recovering separately from different sources	Combining using data fusion techniques
[100]	/	/	*Surveillance System Facebook and Twitter*	/
Proposed Approach	**Annotating manually information**	**Appropriate for real-time**	**Multiple sources (Facebook Twitter)**	**Learning with Neural Network**

Online Listening and Monitoring

Contents were collected from all online channels tracked automatically by the Online Listening Tool, namely Radian6 [92], from websites to social media: Twitter, Facebook, LinkedIn, Instagram, Google+, Youtube and so on. Radian6 tool or any its competitor [3], such as Awario, Brand24.com, Brandwatch, Mention, Keyhole, Socialert.net, SocialPilot.co, Simplify360, etc. of Online Listening or Monitoring tools, is used to collect information, using the search keywords *Boumerdes* and *earthquake* for the earthquake of Boumerdes and the *Algiers* and *flood* keywords for the floods of Algiers. Online listening tools provide the model, which reasonably represents the essentials, namely:

1. Harvesting contents: (as social media conversations, news or any information in the Web);

2. Cleaning data (duplication and replication content): eliminating any dubbed information as retweet and any harmful information;

3. Enabling relevance: obtaining relevant information, thanks to the corpus and neural learning. This corpus is content annotated manually by volunteers;

4. Result analysis: In this step, the results are reviewed and analyzed to ensure the appropriateness of alerting managers.

Main disadvantage of online tools of listening and monitoring is limiting freedoms by monitoring the attitudes of entire populations. The benefits are enormous: as finding details of an ultimate discussion. Predict and prevent the disaster outbreak and make decisions that could save lives, has no commercial value. It is above all a great moral value.

3.2.5 Related works

In 2009, Tobita et al (2009) [32] have started by introducting an integrated crisis simulator, using Web GIS, to community activities of crisis mitigation. In 2012, Fischer and al. [8] introduced Dark and Penumbral Tourism, Mixed or Alternative Realistic Games. In 2015, Tsai et al (2015) [9] introduced floods protection game for education. Followed by Mitsuhara et al (2015) [133] developed a Game-based evacuation drill using real world edutainment. In 2016, Kawai et al [6] developed a system of evacuation drill of tsunami using map of hazard of movement and smart devices. While Power and Robinson (2016) proposed to compare felt reports with tweets about earthquakes.

[3] https://www.quora.com/What-are-the-top-competitors-to-radian6-I-am-looking-for-alternate-measuring-tool-to-use-with-my-clients

3.3 Automated Learning Environment in Managing Disaster

Artificial Neural Networks (ANN), inspired by biological neural networks, are as animals brains. Such systems *learn* to perform tasks, considering examples, without being programmed. A neural network, based on a connected units collection of nodes called neurons, models biological brain neurons. Each connection, biological brain synapses, can transmit a signal from a neuron to another.

3.3.1 Automated Learning Environment: modeling overview

Learning by retro-propagation is a gradient descent method. In a given iteration, the direction of search is given by a negative energy gradient. The pitch is given by a constant chosen by the user (learning velocity). As known, pure gradient descent methods tend to be inefficient, while keeping its great advantage: obtaining a convergence speed faster around the global optimum, as well as a higher convergence accuracy.

The feedforward neural networks (FFNN) are currently used in various applications with great success. Their first advantage is that they do not require a user-specific problem solving algorithm, but they learn from examples, like humans. Their second advantage is that they have an inherent capacity for generalization, ie they can identify and respond to patterns similar to but not identical to those formed for them. There are also some issues with developing a feedforward model, the most important of which is, no guarantee that the model will work well for the problem to be solved [155].

The entire modeling procedure has been studied for introducing methods, leading to always efficient NN models, namely learning data collection, preprocessing and post-processing of data, various activation functions types, weights initialization, learning algorithms and error functions. While all of these factors affect model performance, more attention has been paid to finding the best architecture. This is justified not only by the direct relationship with the performance of the model, but also by the absence of a theoretical basis on how this architecture will be found or on its appearance [155]. The most typical method followed is a process of repetitive trial and error, with examining and comparing a large number of various architectures. This process, time consuming and relying mainly on the human expert experience and intuition, implies a high uncertainty degree. We cite four various approaches, namely:

- The empirical or statistical methods used to study the internal NN parameters effect and choosing appropriate values depending on the model performance [156],
- The hybrid methods such as fuzzy inference [157],

- The constructive and / or pruning algorithms [158] and finally

- The evolutionary strategies.

These methods use the Taguchi's experiments conception principles [159]. Best combining hidden layers number, hidden neurons number, input factors choice, training algorithm parameters, etc. can be identified with these methods even although they tend to be case-oriented.

In the hybrid methods [157], the ANN can be interpreted such as an adaptive fuzzy system or can operate on fuzzy instead of real numbers. In the constructive and / or pruning algorithms that, respectively, add and / or delete neurons of an architecture using a specified criterion to indicate how the ANN performance is affected by the changes [158]. As basic rules, neurons are added when training is slow, and neurons are suppressed when a change in the neuron value does not match at a change in the network response or when weight values associated with this neuron remain constant in a training periods large number.

In evolutionary strategies, topological space is explored by varying the hidden layers number and hidden neurons by applying genetic operators and evaluating various architectures according to an objective function. Constructive and pruning algorithms being gradient descent methods, their convergence towards the global minimum is not guaranteed and can therefore be trapped at a local minimum close to the search space point from launching algorithms.

An artificial neuron, receiving a signal, can process it and report other artificial neurons connected to it. In current neural networks implementations, the signal at a connection between artificial neurons is a real number and the each artificial neuron output is computed by a nonlinear function of its inputs sum. The connections between artificial neurons are called $e$dges. Neurons and artificial edges have a weight, adjusting as learning progresses, increasing or decreasing the signal strength in a connection.

Deep learning allows computer models composed of various processing layers to learn data representations with multiple abstraction levels: this has widely enhanced the art state in object detection, visual recognition and objects, speech recognition and many other areas such as genomics, Sequential Pattern Mining or bioinformatics [37].

3.3.2 Configurations of the Neural Network Parameters

Problem: determining coefficients w_0, w_1 and w_2? To the Error function: If $y = 1$, we want to have $p(x)$ as big as possible. We define the error by : $-lnp(x)$.

Symmetrically, if $y = 0$, we want to have $p(x)$ as little as possible. The error is then $-ln(1 - p(x))$. So, the general formula (3.2) is :

$$error = -y * ln(p(x)) - (1 - y) * ln(1 - p(x)) \tag{3.2}$$

Figure 3.1 shows that a given neuron in a layer k consists of elements such as input flux of all precedent neurons and output flows towards all the following neurons with their respective weights.

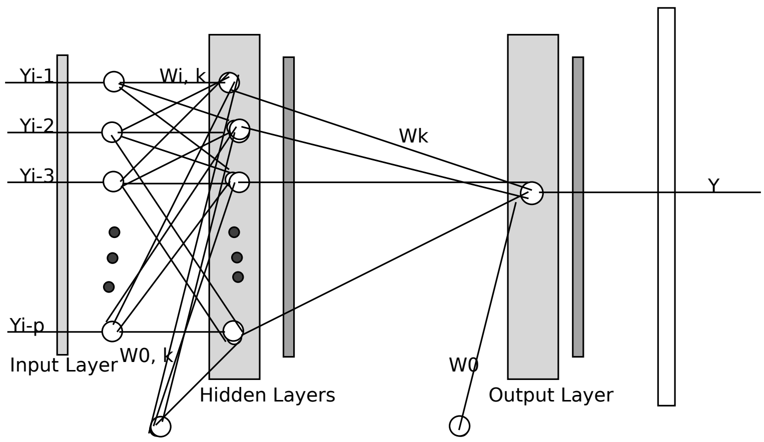

Figure 3.1: Neural Network Structure.

Figure 3.2 shows Feedforward Neural Network Architecture.

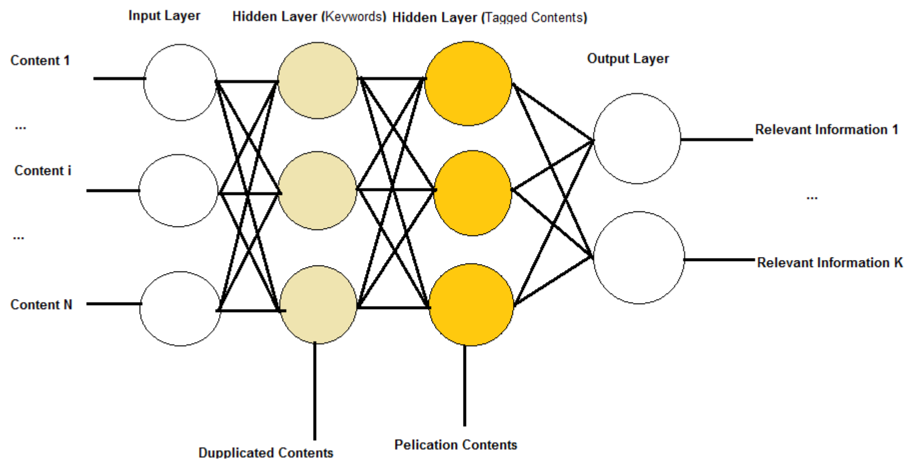

Figure 3.2: Feedforward Neural Network Architecture.

Minimization of the error: Once an error function has been defined, the problem of learning becomes an optimization problem: find the coefficient vector w^* which minimizes the error. In the case of logistic regression, this vector is unique because the error function is convex. The solution vector w^* can be obtained by an iterative algorithm.

Probability of classifier error: Once the optimum w^* coefficient vector is determined, a program (classifier) is available to classify a new individual. To estimate the error probability of the classifier, it is necessary to have an independent test set.

The basic version of frequent pattern extraction is used to search a table in a Content Set whose values are Booleans indicating the presence or absence of a property. O is a finite set of objects. P is a finite set of properties. $\Re$ is a relation on $O\ X\ P$ which makes it possible to indicate if an object x has a property p (noted $x\Re p$) or not. For example, in the case of basket analysis in a supermarket, O is the set of purchase transactions, P is the set of items and $\Re$ is the relationship indicating whether an item is purchased in transaction t.

3.3.3 Manipulating of the Automated Learning Environment

We used the model of Model-View-Controller for event management design. We also extend it to data mining, particularly sequence model exploration. We have could apply it to marketing.

Figure 3.3 shows the launching of Feedforward Neural Network (Automated Learning Environment).

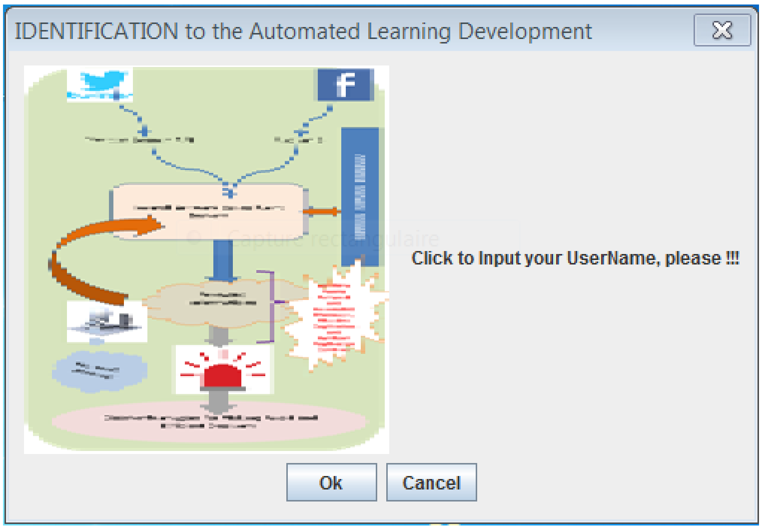

Figure 3.3: Identification in the Automated Learning Environment.

The Apriori algorithm, improved by Savasere [160], is used in Knowledge Discovery in Databases (KDD). We have adapted it to streaming to use social networks data. We have also used and adapted the DIC algorithm of [161] to streaming. Figure 3.4 shows the Architecture of Disaster Management Platform.

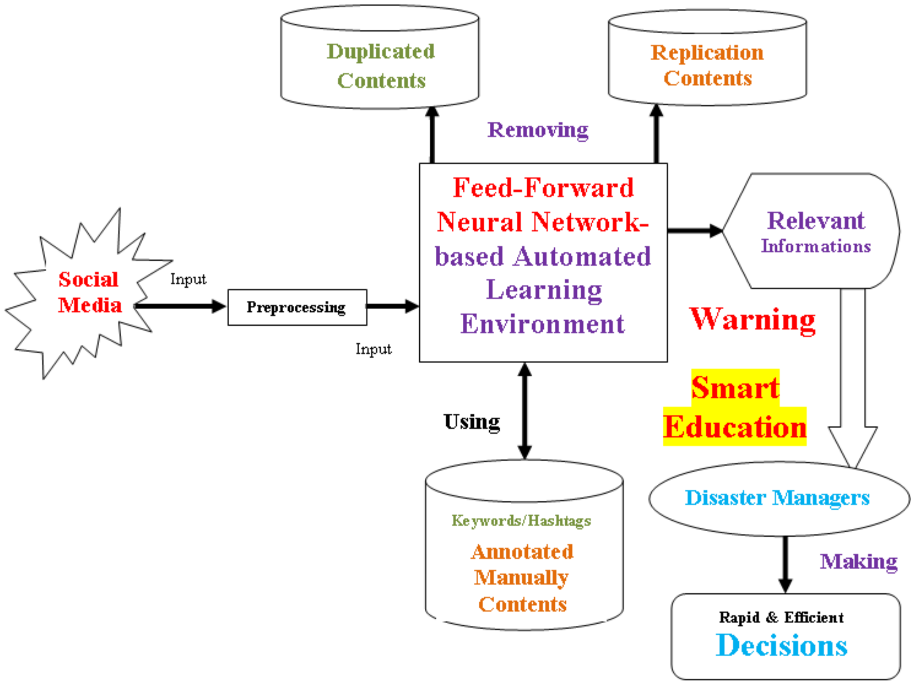

Figure 3.4: Deep Learning-based Automated Learning Environment.

3.3.4 Smart Disaster Education

Education plays a key role, first, in helping citizens to be aware of the dangers, and then, in developping their skills in crisis management. This environment is designed to support an introductory traineeship in managing catastrophe for trainees and future managers. Community members share their knowledge and help one another in preparedness. Evacuation drills are taught in communities, businesses and schools [6, 9, 32, 37, 48, 133].

This environment is designed to support an introductory traineeship in managing disaster for citizens, trainees and future managers. The trainee can use this tool in the following modes:

1 Novice learning environment. To work with this tool, the trainee can use a complete set of automated design and learning tools. One of the functions of the environment is to display visualizations of the trainee's programs. With the help of the environment, the trainee can observe various programs *at work*, experimenting them and gradually learning from his experience, observations and mistakes.

2 Learning environment for beginners. At any point in the job, the trainee can ask this environment to generate (move on) the next step: a new concept or a new build, a build example, a test, an example of a problem solver or a problem to be solved. This tool analyzes domain knowledge and the trainee's model and

provides both the optimal stage and a list of all relevant operations (ie, ready to be applied). The trainee who is not satisfied with the optimal operation suggested by the system can choose any appropriate operation using adaptive hierarchical menus.

3 Online manual rehearsal. At any time during the work, the trainee has a menu to access all previous courses: presentation of any previously learned concept, demonstration of all the examples learned and analysis of any problem explained or resolved. This mode provides access to the material learned from the course as a reference, thereby supporting example-based online help.

3.3.5 Manipulating of the Automated Learning Environment

The trainee must register with username and password. Then, he launch the automated learning environment to defines his own environment. Thus, he can launch it, already configured, to extract content from social media and analyze it. The keywords and manually annotated contents are already operational: we can view them with the *Viewing* menu. Listening and Monitoring is optionally programmed (ready) to *All the Web*. Processing is set to emph Streaming. Alert is set on emph Automatic and Learning on emph Neural learning.

The novice can be satisfied with simply follow the progress of this treatment with *Viewing* menu. We can also viewing relevant content, applied content and replication content.

If he wants to participate (intervene) au processus, he has to change the Learning type with the *Learning* menu, Listening and Monitoring, treatment or alert.

We can also intervene by adding keywords or hashtags in the *Updating Files / Updating Keywords* menu. He can also modify the alert to manual: he must launch the alert himself.

If he is interested in understanding how this tool works, he selects *Content Treatment/Treatment* menu, to insert himself a text in the *Updating Files / Inserting Content* menu.

Thus, he can follow treatment thanks to *Content management* menu for the words number retained after processing the message, obtain content sender or message occurrences number. We can know whether it is accepted as relevant, or rejected.

The session is enregistred: thus, the trainee can, at any time, review all of his work to correct errors in the future.

This Automated Learning Environment enables, at any time, to visualize, thanks to *Viewing*, various used available keywords, manually annotated messages, relevant, duplicate or replication contents.

It enables to work in streaming or just by providing message (especially for novices) in *Client Treatment*.

For Streaming, we have to specify, in *Listening / Monitoring*, whether it is from Twitter (Twitter is chosen optionally), other Social Networks or all the Web.

As for novices, one can enter messages, even update Keywords, in Updating Files, in *Updating Files*. We can be satisfied with an automatic (optional) or manual alert in *Alert* menu. With *File / New* menu, we start a new learning: just enter *Content File* and validate. We will still have this automated learning. We have *Data Mining*, *Neural Learning* and *Deep Learning*. emphData Mining includes *Web Mining*, *Text Mining* and *Sequential Pattern Mining*, which are from the same family. *Neural Learning* consists of *Relevant Information Retrieval* [14] and *Deep Learning* is still under development (being improved).

3.3.6 Discussion about the Automated Learning Environment

Emoticons, blasphemies and interjections are widely used to convey emotions such as happiness, surprise, anger, etc. To identify these features types, we used combining part-of-speech tags in the tagger, compiled lists of blasphemies and interjections on the Web and regular expression patterns for emoticons [14, 15].

Messages from Algeria's target regions are checked for frequency bursts of crisis keywords and processed to identify evidence of a catastrophe. The advantage of our Automated Learning Platform is that it relies on evidence from social networks' first-hand reports. This multi-view model links the input document vector to the multi-view area, based on neural network, whose contextual information is available.

Let $\hat{H}$ be the non-empty set ($\hat{H} \neq \emptyset$) of the terms that we have compiled (terrorist act, explosion, earthquake, etc. for instance), making up the set of keywords or hashtags, for natural and anthropogenic crisises.

Let $e_i \in C_n$, with $i \in [1, N]$, the incorporation of a content of the source message i relevant for, at least, a keyword or a hashtag $h_j \in \hat{H}$ with $j \in [1, M]$. C_n is the set of n contents.

We want to learn a generic space thank to the neural network

$$\hat{E} = \{e_k \; with \; k \; \in \; [1, K]\} \tag{3.3}$$

which normalizes the differences:

$$\hat{E} = [E - \hat{R} - \hat{D}] \tag{3.4}$$

where: $\hat{R}$ is the retweets set, $\hat{D}$ is the duplicate contents set, and helping in best

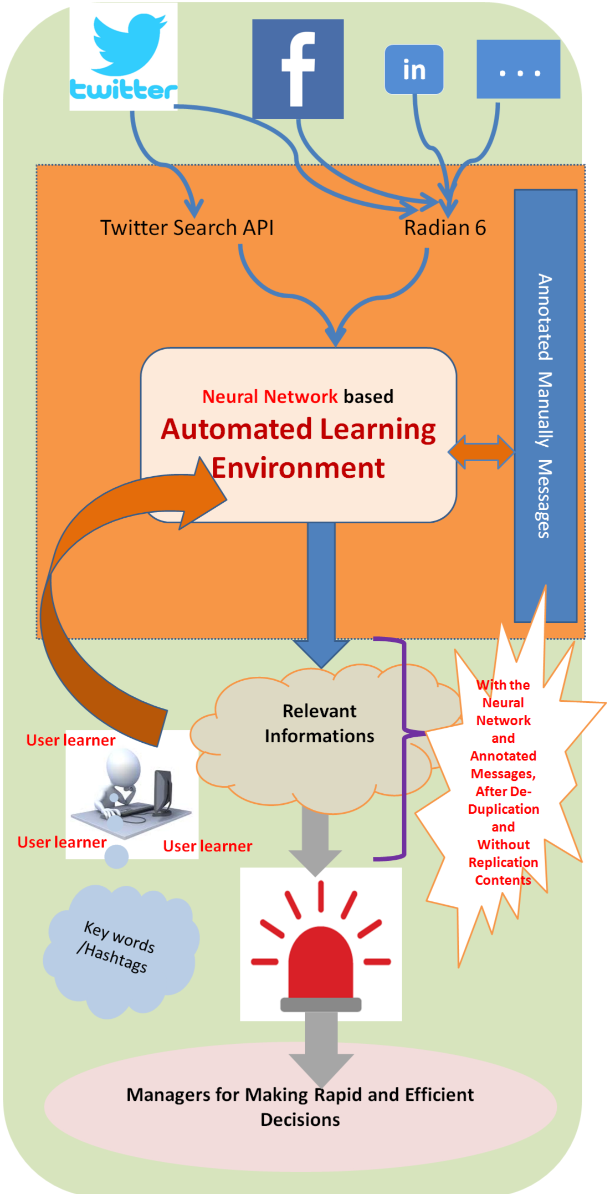

Figure 3.5: Deep Learning-based Automated Learning Environment

recovery of target content.

With the Feed-forward neural network, the transformation of e_i into e_k can be explained by:

$$e_i \rightarrow e_k = \{e_i,\ e_i\ is\ relevant\ for\ h_j,\ e_i \notin \hat{R},\ e_i \notin \hat{D},\ h_j \in \hat{H},\ j \in [1, M]\} \tag{3.5}$$

where $\hat{\mathrm{D}}$ and $\hat{\mathrm{R}}$ represent respectively the set of duplicate contents and re-tweets. The objective is then to maximize the size K of the set $\hat{\mathrm{E}}$.

3.3.7 Performance Evaluation

The objective consists of maximizing the size K of the set E_K. Every effort should be made to increase the number of relevant contents while removing non-informative data (messages manually annotated to cleaning them).

The training data is created from the Coronavirus pandemic, Covid-19.

Tweets were collected thanks to the Twitter Search API and other posts, from various social networks, thanks to the Radian6 tool.

All experiments reported here were performed on this set of data. With our new proposed model and after cleaning and de-duplication, we have the following data set summarized in table 3.7 and figure 3.5.

Table 3.7: Examples of Relevant Content of Global Corona Virus Pandemic (Covid-19) for a Set of Hashtags and Keywords for all social networks.

Model	Global Corona Virus Pandemic (Covid-19)
[14] (Neural Network)	15,619
[15] (Neural Network)	15,619
Our New Approach (FeedForward NN)	16,942

We identified a set of disaster-specific information needs. It's a set of keywords. Data collection and filtering are at the heart of disaster management using social media.

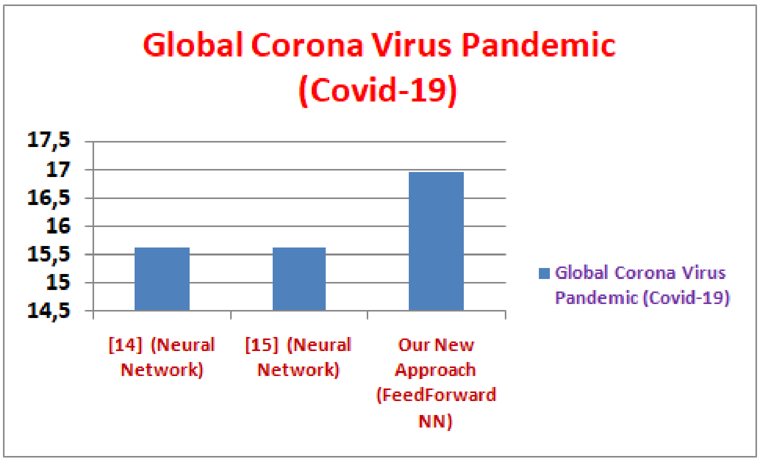

Figure 3.6: Examples of Relevant Content of Global Corona Virus Pandemic (Covid-19) for a Set of Hashtags and Keywords for all social networks.

3.3.7.1 Experimental results

In this section, we present the experiments carried out to compare the performance of models, including our proposed model, tested with the dataset, introduced in the following subsection, which have been preprocessed.

3.3.7.2 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:

$$RMSE = \left(\frac{1}{N}\right) * \sqrt{\sum_{i=0}^{N} (y_i - y_i^*)^2} \tag{3.6}$$

$$MAE = \left(\frac{1}{N}\right) * \sum_{i=0}^{N} (|y_i - y_i^*|)^2 \tag{3.7}$$

$$R^2 = 1 - \left(\frac{1}{N}\right) * \left(\frac{\sum_{i=0}^{N} (y_i - y_i^*)^2}{\sum_{i=0}^{N} (y_i - y_i^t)^2}\right) \tag{3.8}$$

where N represents the number of content flow, y_i is the real content in flow i, and y_i^* is the relevant content flow. y_i^t is the mean value of the relevant content number.

3.3.7.3 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.

3.3.7.4 Results

In this section, we have checked the effectiveness of the proposed feed-forward neural network model against the Neural Network (NN) of our previous models [14, 15]. In the experiment, these automated 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. The final experimental results are presented in table 3.8.

Table 3.8: Examples of Relevant Content of Covid-19 for a Hashtags and Keywords Set from social media.

Model	**RMSE**	**MAE**	R^2
[14] (Neural Network)	17088.3797	18 471	0,3284
[15] (Neural Network)	17088.3797	18 471	0,3284
Our New Approach (FeedForward NN)	16100.9272	19,461.5	0.4645

The number of relevant contents is taken as the historical information for NN and our new approach FFNN. Further, from the RMSE and MAE, it is obviously that FFNN is more accurate than NN since combining the advantages of both. This result indicates that the FFNN model is more suitable to retrieve relevant content than the neural network, the Neural Network model.

3.4 Conclusion

We discussed in this chapter about results of our Deep Learning-based automated learning environment, designed and implemented. Concluding, we presented our Deep Learning-based automated learning environment, fundamentally personal, social, distributed, omnipresent, flexible, dynamic and suitable for disaster education. It is an extension of the real-time alert model used for managing natural or anthropogenic crisises [14, 15]. This environment is based on a semi-supervised inductive technique, using abundant and unlabeled data, notably in the event of a crisis. This is just the start of this automated learning environment: it needs to be improved.

In the next chapter, we will introduce the second enhancing of the Automated Learning Environment, namely: designing and implementing the Hybrid of Deep CNN-LSTM-based Automated Learning Environment (ALE), according to the recommendation of Abiodun et al. cite Abiodun2018.

So, with the richness and in particular the specialization of the different Deep Learning models: that everyone designs their own model according to their own needs.

Science is built up of facts, as a house is built of stones; but an accumulation of facts is no more a science than a heap of stones is a house.

Henri Poincaré

Chapter 4

A Hybrid of Deep Convolutional NN-LSTM Model to enhance Warning, Situational Awareness and Education in Managing Emergency

Summary

4.1 Introduction

The network and Internet traffic volume is expanding daily, with data being created at an exceptionally high rate. Large in veracity, velocity, variety and volume, these data can be characterized as big data.

Using social networking in crisis situations for sharing information in a timely manner [109] has become a standard practice in recent years. With the proliferation of social media, an ongoing event [44] is being discussed on all these channels. There are generally qualitative differences [15, 16] in the information obtained from different sources. To get a complete view of the event, it is important to retrieve contents [16] from multiple sources. However, the challenge facing disaster managers is overwhelming when it comes to retrieving information shared on social media [74], with fine, excellent and net situational knowledge.

Several automated systems [15, 16, 98] have been designed to help disaster managers identify and filter useful information posted on social networking sites. Most of the work, has focused on using a few of social networks (if not the only social network, namely Twitter) as a source of information, only, on a few disaster management phases [109, 44, 98], but few are, concurrently, dedicated to warning [15], crisis education [16] and situational awareness. The design of emergency management systems using different and diverse sources of information (all the Web), and dedicated primarily to warning, situational awareness and disaster education, is a challenge.

Recently applied to large-scale big data analysis, deep learning models have shown remarkable performance [14, 15, 16]. This work proposes a model of hybrid deep CNN-LSTM for detecting efficiently network intrusions based on a CNN and LSTM network. We use CNN for extracting meaningful characteristics from big data and LSTM to retain long-term dependencies among extracted characteristics while preventing overfitting on recurrent connections. The proposed method of hybrid deep CNN-LSTM was compared to traditional approaches in terms of performance on a publicly available dataset, while demonstrating its satisfactory performance.

This new approach allows integrating artificial intelligence technologies, deep learning and social media, in the Emmergency Management Model [17, 93, 164]. It is based on an extension of the Recurrent Neural Network [89] of our previous approach, which is based on the Feedforward Neural Network of our previous approaches [16] used for disaster management and smart disaster education : this experience forms a background for this model. It combines representation training with alert, situational awareness and disaster education, while integrating encapsulations from multiple sources and retrieving information by combining multiple search results, providing some good ideas for that we have extended to improve Emmergency Management.

In this research work [17, 69], we try to identify relevant content dealing with impending catastrophic events. Once this information is retrieved (cleaned of non-informative information), it can be used to update disaster information (warning, situational awareness or disaster education) of disaster managers to make quick and effective decisions that could help people in need or to save lives. Besides, we have provided solutions to the challenges and achieved gratifying results.

Our study has four-fold main contributions.

1. We develop a Hybrid Deep Convolutional LSTM neural network-based model that uses content learning capabilities of multiple sources (all the Web) to automatically and efficiently capture real-time situation awareness reports distributed during large scale catastrophic events, using low-level content learning capabilities to automatically separate relevant content from non-informative information.

2. Using a dataset of keywords/hashtags related to various catastrophic events whether natural or anthropogenic, this model collects, according to their lexical similarity, relevant contents relating to various catastrophic events.

3. Keeping in mind the limitations of the previous work [14, 15, 16, 89, 97], we develop an event-independent model that can be used directly to filter content on multiple source at a time in future events. Experiments on multi-disaster-related contents flows with diverse characteristics show that our proposed model outperforms all the others.

4. Finally, we tested it immediately on the Global Corona Virus Pandemic, Called Covid-19, since January 2020, until nowadays. Then, we conclude and give some future works.

4.2 Deep Learning

Neural learning is carried out by Feedforward (FFNN) or Feedback neural network (FBNN). In Feedforward neural network, we have supervised learning such as Feedforward neural network itself for classification [16], convolutional neural network [18, 47, 141] for image recognition/classification or Residual neural network (ResNets) [152] for image recognition, and unsupervised learning such as Autoencoder [138] for Dimensionality reduction and encoding, Generative Adversarial Network [28] network to generation of realistic false data, reconstruction of 3D models or enhancement of images and with supervised or unsupervised learning as Restricted Boltzmann Machine [138] for dimensionality reduction, feature learning, topic modeling, classification, collaborative filtering or many body quantum mechanics.

In Feedback neural network (FBNN), we have supervised leaning as Recurrent neural network [138] for sequences recognition as precise timing, Bidirectional Recurrent Neural Network [28] for natural language processing (NLP), Long Short-Term Memory [138] for temporal data as stock market values over a period of time, video frames, Fully Connected-LSTM [150] for learning non-linear and complex processes in hydrological or meteorological modeling and Bi-Directional-LSTM [141] through time-natural language processing and language translation.

Neural learning can be trained in a supervised / unsupervised manner by Radial Basic Function Network [151] for M-means clustering, least squares function, function approximation and time series prediction or so not supervised by Kohonen Self Organizing Netowork [151] for dimensionality reduction, optimization problems or clustering analysis. Figure 4.2 shows the classification of Deep Learning models with different features and limitations.

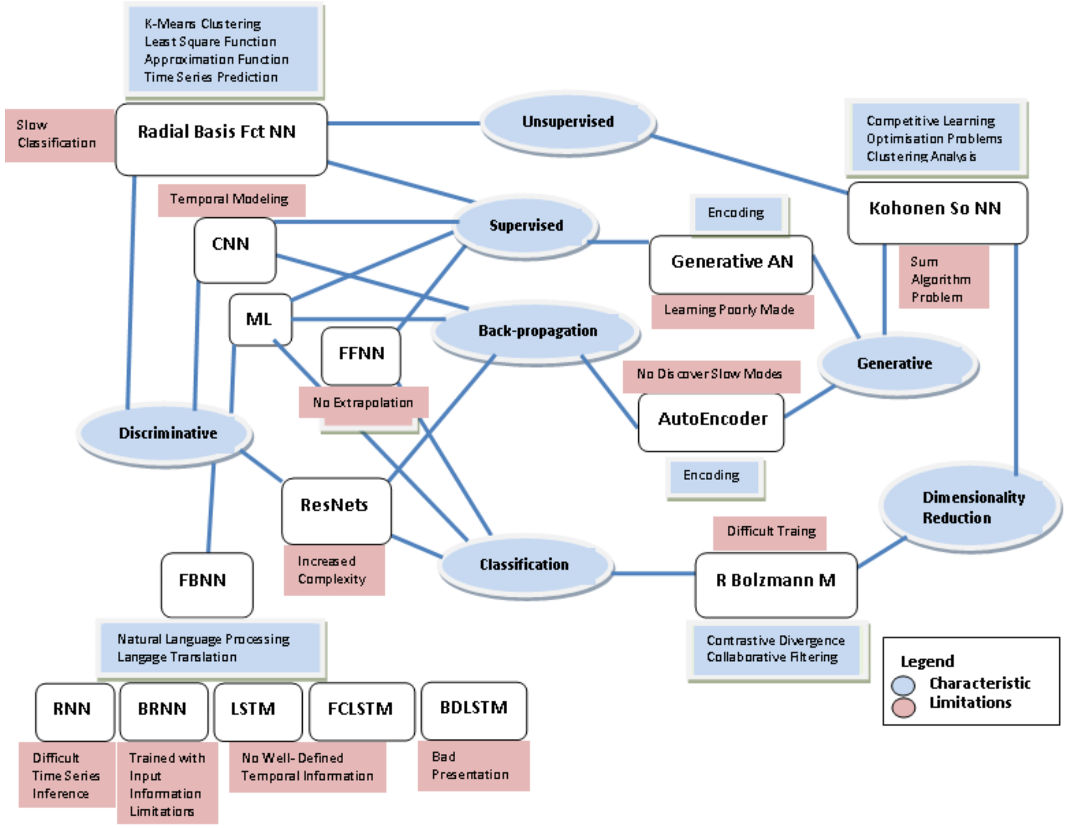

Figure 4.1: Deep Learning Classification with Features And Limitations.

4.3 Proposed Emergency Management Model

4.3.1 Warning, Awareness and Education with Evoluting Pandemic

Online messages contain important information [81] that can also be helpful in making 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 [98], statistical analysis [44], natural language processing [165] to machine learning [15, 16, 109] to computational linguistics [45] have been developed for different purposes, without, fully exploiting this data, despite the existence of some resources, as manually annotated data and standardized lexical resources.

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

Rogstadius et al., (2013) [72] were able to capture distributed situation awareness reports based on Twitter activity during natural disasters. Table 1 gives an overview of recent natural and anthropogenic disasters, and all their damage assessment.

4.3.1.1 Coronavirus Pandemic

Covid-19 is a pandemic of an evoluting infectious disease. It first appears in Wuhan, China, in November 2019 and spreads then across the world. World Health Organization (WHO) asked for essential protective measures 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. Besides, it has social and economic instability effects. It is also the pretext for the online dissemination of erroneous or conspiracy theory information. Luckily, with approximately 2 percent of the cases detected, the provisional death rate is lower than in previous coronaVirus epidemics. About roughly 110,270,288 cumulative cases were confirmed globally as of February 19, 2021, including 62,077,509 individuals healed and 2,439,834 dead. The contaminations number with the CoVid-19 corona Virus continues to increase to this day.

More than 4000 variants of SARS-CoV-2 have been identified around the world: a natural process as the virus acquires mutations over time to ensure its survival. British variant or B.1.1.7 (called VOC 202012/01 or B.1.1.7) : 64% more lethal.

The britanic variant was reported by UK authorities on December 14, 2020 and has increased sharply cases on the island. It is not only more contagious but also 64% more deadly than the classic coronavirus.

South African variant (Called 501Y.V2): 50% more transmissible. It is 1.5 times more contagious than SARS-COV-2, but not more lethal. It seems to reduce the vaccines effectiveness, notably with the mutation of E484K. It tends to show that people infected with the new coronavirus South African variant have best immunity to other mutations in the virus.

Two Brazilian variants from the Amazon: the first variant, B1.1.248, was detected in January in Japan in a Brazillian family from the Amazon. This variant is more contagious. Among 18 coronavirus variants circulating in Amazonas, P.1, a second variant, has appeared. It is also said to be 1.1 to 1.8 times more likely to cause death.

Table 4.1: Latest catastrophic events.

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

4.3.1.2 Warning, Awareness and Education

We suggest a new emergency management model focused on a Hybrid neural networks for warning, situational awareness, and education on social networks in this paper. It is based on an extension of Recurrent neural network [89] of our previous approach used to improve Fraud Detection and Time Series Forecasting. This last work is based on the Feedforward [15, 16] used in our previous works for disaster management and disaster education. This experience forms a background for this Emmergency Management Model, based on RNN trained with LSTM used because of its ability to learn long term dependencies. This Emergency management model combines representation training with warning, situational awareness and disaster education, while integrating encapsulations from multiple sources and obtaining information by combining multiple search results (on the web).

Table 4.2: Comparative table of all techniques used with Situational Awareness.

Situational Awareness Approaches	Identification Methods
[72]	CrisisTracker: Crowdsourced Twitter curation for disaster awareness
[74]	Summarization with social-temporal context
[75]	Building a Tweet Summarization Dataset Using a TREC Track
[76]	Semi-automated artificial intelligence-based classifier for Disaster Response
[79]	Twitter activity Multi-scale analysis after, during, and before Hurricane Sandy
Our New approach	**Based on Hybrid of Deep CNN-LSTM**

Whether it's Twitter, Facebook, Viber, Messenger, any forum or anything in the Web, these are platforms where people often express emotions. The data available on social networks differs in many ways from other Web sources (press articles, for example). These messages use less formal language, may contain words from more than one language, may have various grammatical and spelling errors, and are, for the most part, unstructured, fuzzy and short-lived [15, 16]. Their length and content vary considerably [88]. We detected emotions using features, such as: interjections, blasphemy, emoticons and the general feeling of the message, widely used by individuals to convey emotions such as danger, surprise, happiness, etc. To identify these features, we used a combination of par-of-speech (POS) tags, compiled lists of interjections and blasphemies upon the Web and patterns of regular expression for emoticons.

Table 4.3: Comparative table of all techniques and methods used in Models including our approach.

Ref	**Identification Methods**	**Used OSN**
[70]	Flood Disaster Game-based Learning	Twitter
[71]	Educational Purposes in Higher Education Faculty with Special Reference	Twitter
[74]	Summarization with social-temporal context	Twitter
[75]	Capitalizing on a TREC Track to Build a Tweet Summarization Dataset	Twitter
[76]	Semi-automated artificial intelligence-based classifier for Disaster Response	Twitter
[15]	Based on Artificial Neural Network (ANN)	Twitter/ Facebook
[16]	Based on FeedForward Neural Network (FFNN)	All the Web
[89]	Based on Recurrent Neural Network (RNN)	All the Web
[97]	Based on LSTM	All the Web
Our New approach	**Based on a Hybrid of Deep Convolutional LSTM (ConvLSTM)**	**All the Web**

Our emergency management model based on a real-time recurrent neural network is best suited to situational awareness (see table 2). It uses multi-source content (from all the Web) (see table 3) learning capabilities to automatically and efficiently capture distributed real-time situational awareness reports during large-scale catastrophic events, 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).

Table 4.4: Comparative table of all techniques and methods used in Models with education including our approach.

Disaster Education Approach	**Identification Methods**
[70]	Flood Disaster Game-based Learning
[71]	Educational Purposes at the Higher Education Faculty with Special Reference
Our Previous approach [16]	Based on FeedForward Neural Network (FFNN)
Our New approach	**Based on Hybrid of Deep CNN-LSTM**

Contents were collected from all online channels tracked automatically by the Online Listening Tool, namely Radian6 [88] from websites to all social media, such. Actually, many networking platforms allow access to their data via Application Programming Interface (API) [88]. Online listening tools provide the model, which reasonably represents the essentials, namely: harvesting contents, cleaning the data of non-informative information, enabling relevance thanks with the learning corpus obtained thanks to the tagged messages, and analyzing the results (verification and analysis of the results carried out in order to ensure adequacy to build disaster information such as warning, situational awareness and/or disaster education).

4.3.2 New Model of Emergency Management

We present our new network model, ConvLSTM. The LSTM layer has been shown to be powerful in handling temporal correlation (too much redundancy for spatial data), its extension (of LSTM) has convolutional structures in both input-state and state-to-state transitions will solve this problem [166]. By stacking several ConvLSTM layers and forming a coding-prediction structure, we come to construct a network model for these spatiotemporal sequence prediction problems.

The goal of crisis forecasting is to use the previously observed social networking sequence to forecast an event in a local region (for instance, Algiers, London, or Paris). This problem can be considered as a spatiotemporal sequence prediction.

Suppose we observe a dynamic system represented by an MxN grid made up of M rows and N columns. Within each cell of the grid, there are P measures (word, bias) which vary over time. The observation can be represented by a tensor X belonging to R_PxMxN, with R denoting the observed traits domain. If we record the observations periodically, we will obtain a sequence of tensors

$$X_1, X_2, ..., X_t.$$

The problem with spatiotemporal sequence prediction is to predict the most likely sequence of length K, in the future, given previous J observations, including the current sequence:

$$\hat{\mathbf{Y}}_{t+1}, ..., \hat{\mathbf{Y}}_{t+K} = argmax_{\mathbf{X}_{t+1},...,\mathbf{X}_{t+K}}$$

$$p(X_{t+1}, ..., X_{t+K}|Y_{t-J+1}, Y_{t-J+2}, ..., Y_t)) \tag{4.1}$$

For crisis forecasting, the observation at each time stamp is a 2D map. If we divide the map into non-tiled, non-overlapping patches and visualize the pixels inside a patch as its measurements, the problem is naturally a spatiotemporal sequence prediction problem. We note that our spatiotemporal sequence prediction problem is different from the one-step time series prediction problem because the prediction target of our problem is a sequence that contains both spatial and temporal structures.

The input to the network is a content e, as :

$$e = (w_1, w_2, ..., w_t) \tag{4.2}$$

containing words $w_i \in \mathbf{W}$ each coming from a finite vocabulary V. is the set of contents issued from the social media.

How to determine the coefficients $w_0, w_1, ..., w_n$? To the Error feature: if y = 1, we want p(x) to be as big as possible. We define the error by:

$$-ln(p(x)) \tag{4.3}$$

Symmetrically speaking, we want p(x) as small as possible if y = 0. The error is then:

$$-ln(1 - p(x)) \tag{4.4}$$

So, the general formula is :

$$error = -y * ln(p(x)) - (1 - y) * ln(1 - p(x)) \tag{4.5}$$

Once an error function has been defined, the problem of learning becomes an optimization problem: find the coefficient vector w^* which minimizes the error. In the case of logistic regression, this vector is unique because the error function is convex.

Once the optimum w^* coefficient vector is determined, a program (classifier) is available to classify a new individual. For estimating classifier error probability, it is required to have a set of independent test.

4.3.2.1 Convolutional Neural Network

CNNs are regularized variants of multilayer perceptrons, usually meaning totally linked networks, where each neuron in one layer is linked to the next layer [17, 18, 47, 93, 142, 164].

The *fully-connectedness* of these networks makes them susceptible to overfitting information, where traditional methods of regularization, include adding to the loss function, some form of magnitude measurement of weights.

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

$$conv(a^{[l-1]}, K^{(n)})_{x,y} = \tag{4.6}$$

$$\psi^{[l]}(\Sigma_{i=1}^{n_H^{[l-1]}} \Sigma_{j=1}^{n_W^{[l-1]}} \Sigma_{k=1}^{n_C^{[l-1]}} K_{i,j,k}^{(n)} * a_{x+i-1,y+j-1,k}^{[l-1]} * b_n^{[l]}) \tag{4.7}$$

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

Although CNNs take a different approach to regularization. Convolutionary networks, 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 field known as the receptive field (see Figure 1). CNNs use very little pre-processing: they learn the filters that were hand-engineered in conventional algorithms [47].

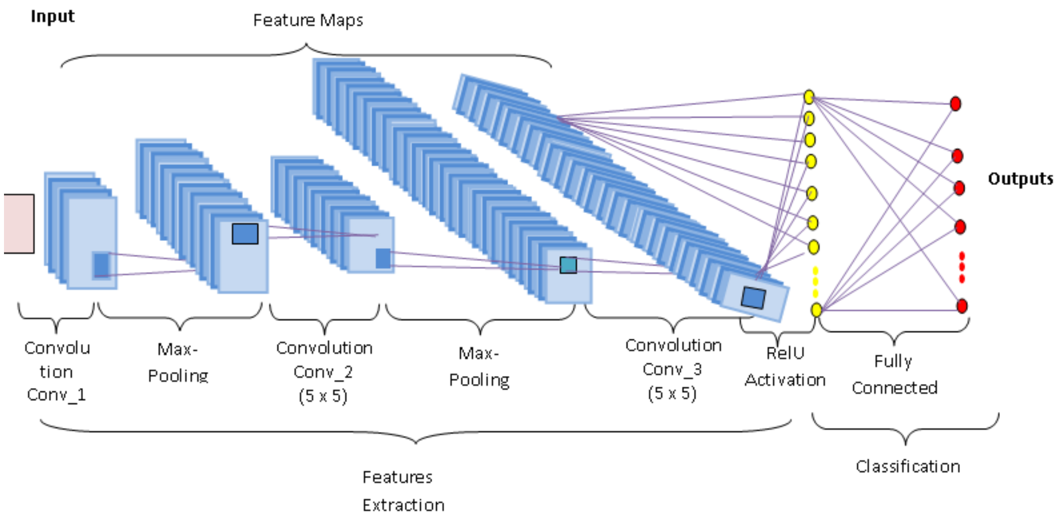

Figure 4.2: The structure of Convolutional NN.

Artificial intelligence (AI) is a combination of deep learning and reinforcement learning [104], represented mathematically, as :

$$AI = RL + DL \tag{4.8}$$

where : AI represents Artificial Intelligence, RL represents Reinforcement Learning, and DL represents Deep Learning.

A feedforward neural network (FFNN) is an classification algorithm, organized in layers, as human neurons. Each unit in a layer (known as node) relates to all other units in these layers. These layers connections can have a various weight measuring the potential amount of the network knowledge. In the network, information processing requires data entry from the input units and flows through the network, flowing from one layer to the other before the output units. If the neural network operates normally (as a classifier), then there will be no feedback [104] between layers. Logically, FFNN can handle tasks based on first come first serve input bases. As for the feed-backward NN (FBNN), it can use internal state memory to process sequence of data inputs, such as Recurrent Neural Network (RNN).

Recurrent Neural Networks (RNNs), which are part of the FFNN class, include recurrent edges to connect adjacent time steps. Figure 1 shows the well-known Elman, recurrent neural network [138], according to Jordan's original idea [167].

Table 4.5: Overview of the coronavirus pandemic (Covid'19) and their damage (affected, dead and healed) since May 31^{st}, 2020, in Algeria.

Period	**Affected**	**Death**	**Healed**
May 31^{st}, 2020	9,394	653	
June 06^{th}, 2020	10,05	698	
July 21^{st}, 2020	24,278	1,1	
August 24^{th}, 2020	41,858	1,446	
October 1^{st}, 2020	52,658	1,783	36,958
November 10^{th}, 2020	63,446	2,077	42,626
November 12^{th}, 2020	64,257	2,093	42,980
March 16^{th}, 2021	115,410	3,040	79,994

The formula for the current state is

$$h_t = f(h_{t-1}, x_t) \tag{4.9}$$

Applying activation function tanh:

$$h_t = tanh(\sigma_{hh}.h_{t-1} + \sigma_{xh}.x_t) \tag{4.10}$$

σ is weight, h is the single hidden vector, σ_{hh} is the previous hidden state weight, σ^{xh} is the current input state weight, *tanh* is the funtion of Activation, that introduces a Non-linearity squashing the activations to the range [-1,1]. Output:

$$y_t = \sigma_{hy}.h_t \tag{4.11}$$

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

According to Figure 1, we can use two equations to describe this type of LSTM. All calculations necessary, at each time step, on the forward pass is:

$$h_t = \alpha(\sigma_{hx}.x_t + \sigma_{hh}.h_{t-1} + b_h)y_t = \beta(\sigma_{yh}.h_t + b_y) \tag{4.12}$$

where the σ terms denote weight matrices (e.g. σ_{hx} is the weights matrix between the input and hidden layers).

The b terms denote bias vectors (e.g. b_h is hidden bias vector) which enable, each node, to learn an offset.

α denotes the hidden layer function.

In general, α is an element-wise application of a sigmoid function and β is the function of the output layer.

4.3.2.2 Long Short-Term Memory (LSTM) Network

LSTM referred to a neural network standard kind, extended over time, with edges feeding into the next time step, rather than the next layer. It is constructed to sequences recognition (ie a speech signal or a text). It has cycles indicating short-memory presence in the net. LSTM, like a hierarchical network, its entry requires hierarchical processing, in the form of a tree: no time to enter the sequence.

It has achieved remarkable success in sequential learning problems.

Although RNN is not deep in space, it is inherently deep in time since each hidden state is function of all previous states [138].

It can model the data series such that each sample is based on previous data, as difficult training due to issues of disappearance of gradient at propagating errors over many phases [168].

In order to overcome this flaw, LSTM is a promising RNN architecture for sequence learning [169]. Relative to RNN Elman, LSTM introduces the memory cell, a computing unit replacing conventional artificial neurons in the hidden layer.

LSTM networks, a kind of sophisticated RNN, whose name, using specific units, help to remember past data in memory cell, which is a component of LSTM units keeping information for a long time, and, thus solving RNN's gradient disappearance question. LSTM, training the model using back-propagation, is well-suited to classify, process and forecast time series, thanks to time lags of unknown length.

The mathematical definition of the calculation of the LSTM model is 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.

   In an LSTM network, three gates are present (see Figure 4.3.2.3:

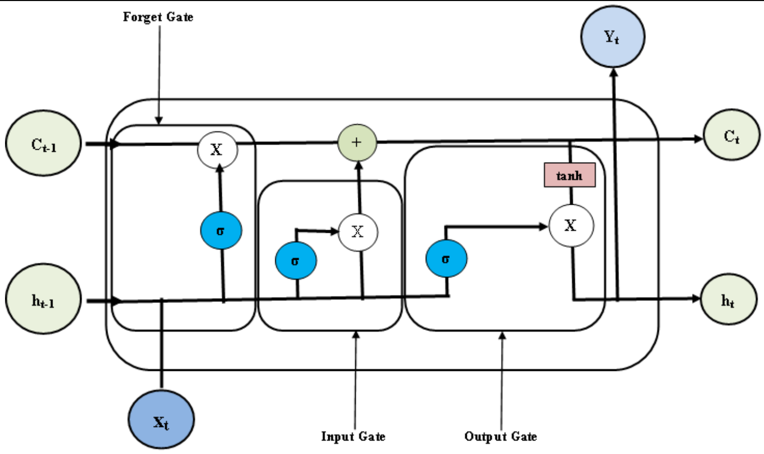

Figure 4.3: Overview of the LSTM Gates

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4.3.2.3 Hybrid of Deep Convolutional neural network-LSTM Automated Learning Environment

Here is the functioning of Hybrid of Deep Convolutional neural network-LSTM Automated Learning Environment (see Figure 4.3.2.3).

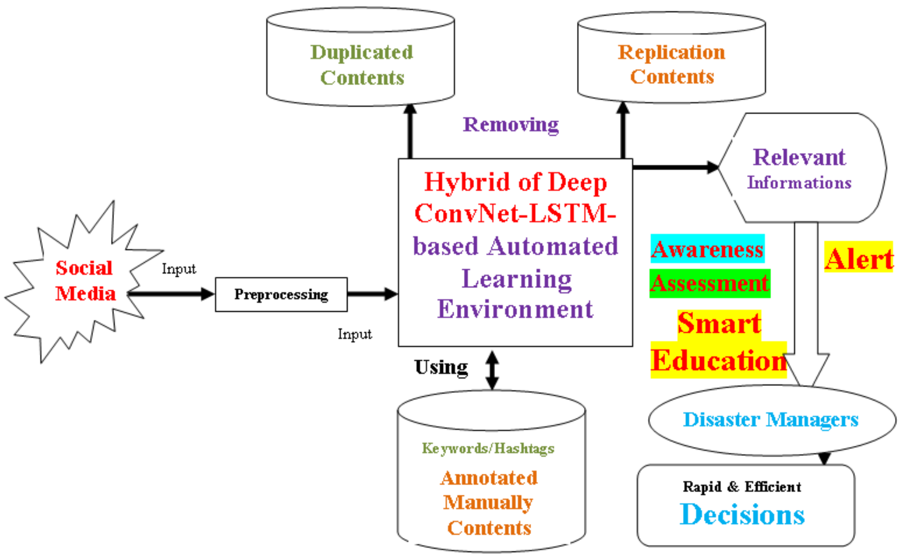

Figure 4.4: Overview of the Architecture of our Deep ConvLSTM

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Here is the Hybrid of Deep Convolutional neural network-LSTM (see Figure 4.3.2.3).

$$i_t = \sigma(\omega_{ix}.x_t + \omega_{ih}.h_{t-1} + b_i) \tag{4.13}$$

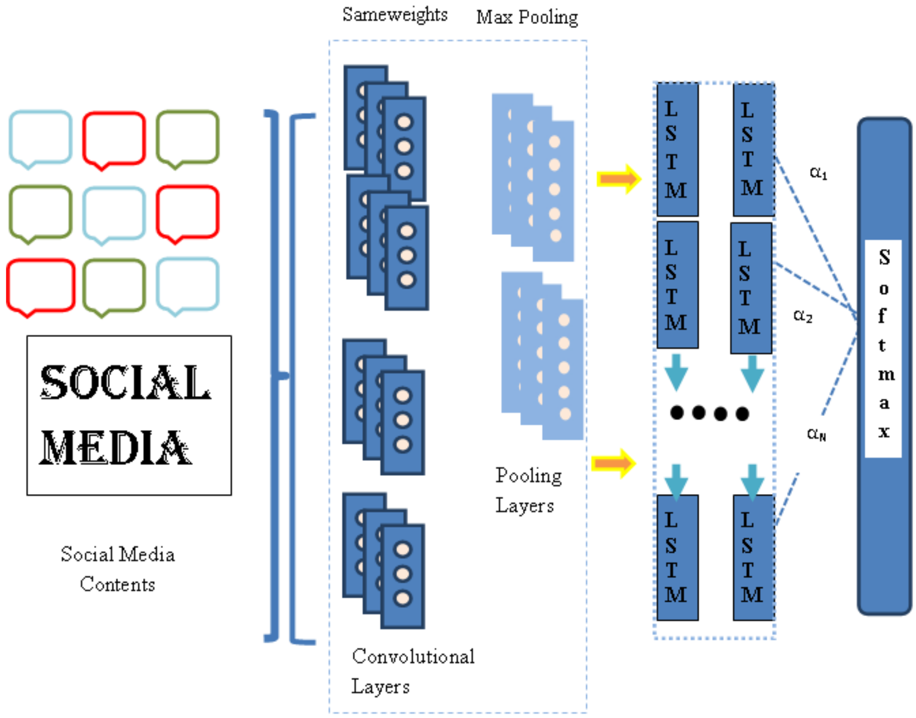

Figure 4.5: Overview of the Architecture of our Deep ConvLSTM

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$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(\omega_{cx}.x_t + \omega_{ch}.h_{t-1} + b_c) \tag{4.14}$$

2. Forget gate - using sigmoid, find information to delete from the block. It analyses the previous state h_{t-1} and material input xt for each number in cell state ct-1, and selects the number from 0 (omitting it) and 1 (keeping it)..

$$f_t = \sigma(\omega_{fx} * x_t + \omega_{fh} * h_{t-1} + b_f) \tag{4.15}$$

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.

$$j_t = \sigma(\omega_{jx} * x_t + \omega_{jh} * h_{t-1} + b_j \tag{4.16}$$

$$h_t = j_t \odot \tanh(c_t) \tag{4.17}$$

where

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

The entire Deep ConvLSTM modeling procedure has been studied with the aim of introducing systematic methods leading to always efficient models, namely the collection of learning, preprocessing and post-processing of data, various types of initializing weights, algorithms for learning, activation and error functions. Although all of these factors affect its performance, increased attention has been focused on finding the best architecture.

4.3.3 Foundation of Deep ConvLSTM

We have a recurrent neural network with hidden layers taking as input contents as: $e = (w_1, ..., w_i, ..., w_n)$ contains words each coming from a finite vocabulary.

Let :

$$e_i \in C_n, with\ i \in [1, N]\ and\ e_i = (w_{i1}, w_{i2}, ..., w_{in}) \tag{4.18}$$

containing words each coming from each a finite vocabulary V, the incorporation of a content of the source message i relevant for, at least, a keyword or a hashtag :

$$H_j \in \mathbf{H} \quad with\ j \in [1, M] \tag{4.19}$$

With the neural network, we want the learning of a generic space, as:

$$\mathbf{E} = \{e_k; \quad k \in [1, K]\} \tag{4.20}$$

which normalizes the differences:

$$E = [\mathbf{E} - \mathbf{RDF}] \tag{4.21}$$

where :

$$\mathbf{RDF} = [\mathbf{R} + \mathbf{D} + \mathbf{F}] \tag{4.22}$$

Thanks to the Hybrid of Deep Convolutional neural network-LSTM, the transformation of e_i into e_k can be explained by:

$$e_i \rightarrow e_k = \{e_i; such\ as\ e_i\ is\ relevant\ for\ H_j\ and\ w_i;\} \tag{4.23}$$

$$H_j \in \mathbf{H}\ with\ j \in [1, M]$$

where:

$$w_l \in \mathbf{W}; with\ l \in [1, L]; e_i \in [\mathbf{R} + \mathbf{D} + \mathbf{F}]; \tag{4.24}$$

$$with\ k \in [1, K]; i \in [1, N]$$

D, **R** and **F** represent respectively the set of duplicate retweets, duplicate contents and false alerts.

W represents the set of words of a language that L is its dimension.

The objective consists of maximizing the size K of the set E_K.

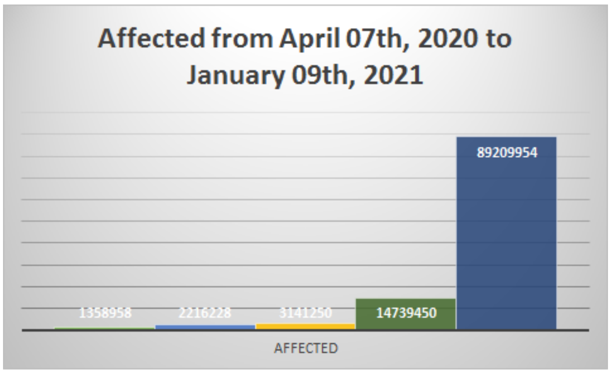

Figure 4.6: Global Assessment of the Coronavirus Pandemic for the Period of April 07th, 2020 to January 09th, 2021 (a).

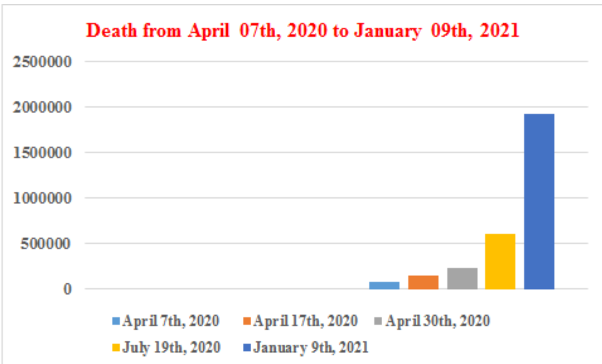

Figure 4.7: Global Assessment of the Coronavirus Pandemic for the Period of April 07th, 2020 to January 09th, 2021 (b).

Social media data help respond to disasters [79]. During crisis events, citizens easily turn to social networks to confide in, quickly disseminate information and learn useful insights. Social media improves people's knowledge of the situation, facilitates the dissemination of information (especially in emergencies), enables to learn useful insights, early warning systems and helps coordinate relief efforts. In addition, the spatio-temporal dissemination of messages relating to crises facilitates real-time monitoring and evaluation of this disaster, before, during and after events [79].

Most disaster publications assume that the media are the most important mitigation tool for managers because their content creates awareness of disasters and risks. Victims, volunteers and relief organizations are increasingly using social media to report and take action on high profile events [72]. Researchers show a correlation between per capita social media activity and disaster damage, making it easy to quickly assess [79].

4.3.4 Warning and Alert

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

4.3.5 Situational Awareness

In crisis situations, the essential decision making needed depends heavily on the availability, quality, and timeliness of relevant information available to decision-makers. Our approach in designing situational awareness systems is to design warning model that consider situations and events as fundamental entities. An important aspect of emergency situation awareness using social media consists to detect and characterize the emergency-related event while it is not still known (we will be the first to know). Thus, we will be better equipped to take all the precautions and the luck on our side. In the evolving pandemic, knowing and especially applying, first of all, wearing the bib and making physical/social distance, will play a significant role in saving lives. This will serve as first operations, among others, to apply. Physical/social distancing is significantly influenced by situational awareness and disaster education [170]. Thus, it can be inferred that increasing situational awareness, in times of public health crisis, using disaster education, can significantly increase the protective health behavior adoption and contain the infectious diseases spread. (See Figures 5, 6 and 7).

4.3.6 Disaster Education

This Model is designed to support an introductory traineeship in managing emergency for citizens, trainees and future managers. Thus, the trainee can use this tool in three modes [16]. Novice Mode permits him to use a complete set of automated design and learning tools, such as observing of various programs at work, experimenting them and gradually learning from his experience, observations and mistakes. Beginners

Mode permits him, at any point, to ask this tool to generate (move on) the next step. This tool analyzes knowledge and provides both the optimal stage and a list of all relevant operations. Not satisfied with the proposed operation, he can choose himself any appropriate operation using adaptive hierarchical menus. In the Online manual rehearsal Mode, at any time during the work, the trainee has a menu to access all previous courses : presentation of any previously learned concept, demonstration of all the examples learned and analysis of any problem explained or resolved. This mode provides access to the material learned from the course as a reference, thereby supporting example-based online help.

During public health emergencies, educational information [170] plays a important role in improving situational awareness.

The Covid-19 pandemic is an emerging infectious disease [171] caused by the coronaVirus SARS-CoV-2.

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

By adapting educational programs designed by many academic institutions, hospitals, professional organizations, governments, and non-governmental organizations, this Emergency Model is also designed to support an introductory traineeship to prepare the health system and health personnel to meet the health needs of populations affected. It consists of Standardizing good practices by developping the *core competencies* of essential knowledge and skills for disaster health workers.

For disaster health workers, hundreds of skills were trained and certified by government and professional organizations and corporations [172], namely :

- competencies tailored to a given position or function during a disaster;
- competencies focused on skill level rather than role or function;
- competencies based on specific roles as well as proficiency levels;
- graded emergency nursing skills according to the stages of the disaster management process;
- specified competencies as *core* competencies for various target groups, and

- *transversal skills* applicable to all workers of health.

Unfortunately, imprecise and inconsistent terminology and structure are evident throughout the reviewed competency sets. It is necessary of Universal acceptance and application of these competencies. This approach aims developing a standardized terminology and framework for manipulating competency sets, accepted and adapted universally, for health professionals.

4.3.7 Performance Evaluation

Standard relevance queries and judgments. The objective consists of maximizing the size K of the set E_K. The training data is created from the Coronavirus pandemic, Covid-19. This information, easily obtained using the neural network, is manually annotated by volunteers. In order to show the effectiveness of our model, we examined specific events of Covid-19 and post-event messages on several social media : Twitter, Facebook, LinkedIn, Instagram, Google+, Youtube, Messenger, Viber and so on.

All experiments reported here were performed on this set of data. With our new proposed model and after cleaning and de-duplication, we have the following data set summarized in table 4.6 and figure 4.3.7.

Table 4.6: Examples of Relevant Content of Global Corona Virus Pandemic (Covid-19) for a Set of Hashtags and Keywords for all social networks.

Model	**Global Corona Virus Pandemic (Covid-19)**
[14] (Neural Network)	15,619
[15] (Neural Network)	15,619
[16] (FeedForward NN)	16,942
[89] (Recurrent NN)	17,846
[97] (LSTM)	18,228
Our New Approach (ConvLSTM)	19,925

We identified a set of disaster-specific information needs. It's a set of keywords. Data collection and filtering are at the heart of disaster management using social media. Every effort should be made to increase the number of relevant contents while removing non-informative data (messages manually annotated to cleaning them).

To refine the results, generally, different topics behave better with different functions and keywords/hashtags. The goal was to identify all relevant content relative to the predefined keywords. The overall effectiveness of a large-scale disaster emergency response is a difficult entity to measure. Every disaster is different and every answer is different.

In fact, similar events offer totally different results in their aftermath. For instance, a category four flood in Algiers, Algeria's capital, will cause much more damage than

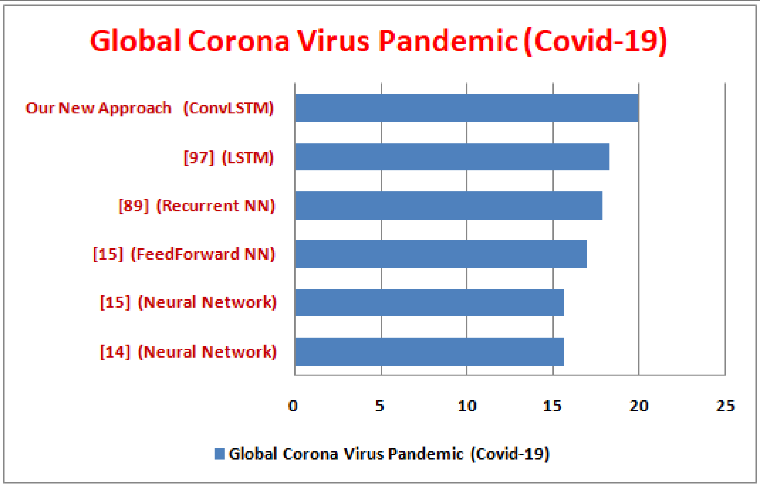

Figure 4.8: Examples of Relevant Content of Global Corona Virus Pandemic (Covid-19) for a Set of Hashtags and Keywords for all social networks.

a category two flood in a smaller town. Besides, the emergency response, in rural region, is different from that to Bouira earthquake, in a regional city, according to Brown et al. [173]. Appropriate indicators must be used and interpreted correctly to accurately assess the overall response to these incidents. Although there are many theories, it is very difficult to evaluate the effectiveness of a method thanks to the inherent irregularity of disasters. No two disasters are alike, so it is hard to tell if one method is better than another. In a crisis, the response should not be, neither in doubt, nor a test of new ideas, with all the confusion inherent, but rather a well-tested and carried out response [173]. Using social networks' disaster datasets leads to vague words, contradictory and incomplete details, and general uncertainty. When modeling and simulation are necessary for a cheap and time-efficient system observation method, using disaster data is quick and difficult at best and also for testing several inputs and different results. Implementing a simulation for an observer draws the benefits of simulation, in terms of cost and time, as one of the best reasons [173]. Otherwise, the pilot alert system presented here consists of validating the research bases carried out as part of this work.

4.3.7.1 Experimental results

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

4.3.7.2 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:

$$RMSE = \left(\frac{1}{N}\right) * \sqrt{\sum_{i=0}^{N} (y_i - y_i^*)^2} \tag{4.25}$$

$$MAE = \left(\frac{1}{N}\right) * \sum_{i=0}^{N} (|y_i - y_i^*|)^2 \tag{4.26}$$

$$R^2 = 1 - \left(\frac{1}{N}\right) * \left(\frac{\sum_{i=0}^{N} (y_i - y_i^*)^2}{\sum_{i=0}^{N} (y_i - y_i^t)^2}\right) \tag{4.27}$$

where N represents the number of content flow, y_i is the real content in flow i, and y_i^* is the relevant content flow. y_i^t is the mean value of the relevant content number.

4.3.7.3 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.

4.3.7.4 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 table 4.7.

In this section, we have checked the effectiveness of the proposed ConvLSTM 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.

Table 4.7: Examples of Relevant Content of Covid-19 for a Hashtags and Keywords Set from social media.

Model	RMSE	MAE	R^2
[15] (Neural Network)	17088.3797	18 471	0,3284
[16] (FeedForward NN)	16100.9272	19,461.5	0.4645
[89] (Recurrent NN)	13359.4722	19,962.5	0.4805
[97] (LSTM)	16704.4894	19,557	0.5064
Our New Approach (ConvLSTM)	21070.1960	12,809.5	0.6998

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

4.4 Conclusion

This work is based on extracting, in real time, information on catastrophic events from multiple sources (*on the Web* and to immediately alert disaster managers so that they can make quick and effective decisions that could, perhaps, save lives. Indeed, we propose a new ad hoc real-time alert model for the management of disaster, whether natural or anthropogenic, based on a new multi-view recovery model from multiple sources. Such an approach is really useful for local disaster monitoring, but also for helping to make appropriate decisions.

1. We have developed a neuron-based model that uses low-level content learning capabilities to automatically separate relevant information from redundant (*eg. retweets for Twitter*) or abusive information (*at the level of the community, for example*).

2. This model, based on a Hybrid Deep Convolutional LSTM, uses the learning capabilities of multiple source content (*all the Web*) to automatically retrieve relevant information using a set of keywords and hashtags respectively, related to various catastrophic events, whether natural or anthropogenic.

3. Keeping in mind the limitations of the previous work [14, 15, 16, 89], we have developed an event-independent alert model that can be used directly to filter

content from multiple sources at future events. Experiments on multi-disaster-related content flows with diverse characteristics show that our proposed model outperforms views in previous approaches. While our approach filters content (*Twitter tweets and Facebook posts at once*).

4. Once we developed this real-time alert model, we immediately tested it on the actually Corrona virus Pandemic (Covid-19).

5. We have also proposed a warning network propagation scheme that will enable disaster managers to make effective decisions quickly and effectively to save lives.

"A scientist can be productive in various ways. One is having the ability to plan and carry out experiments, but the other is having the ability to formulate new ideas, which can be about what experiments can be carried out by making (the) proper calculations. Individual scientists who are successful in their work are successful for different reasons."

Linus Pauling

General Conclusion & Perspectives

This chapter closes this thesis report which deals with the consideration of real-time disaster management using social networks and in particular machine learning to extract new relevant messages that arrive in social networks. Throughout this report, we have presented disasters, disaster management, the different models of disaster management. We also presented social networks and monitoring tools for its content, which is continually updated by people. We have presented all classification techniques, from SVM to machine learning. Then we improved these classic feasibility conditions to extract relevant content, using artificial intelligence techniques and automated learning.

Summarizing Chapters

The state of the art of retieving relevant contents of disaster from social media consists of the overview of disaster and disaster management, social networking and models of retieving information from social networks: it is presented in the Chapter 1. First of all, this chapter recalls the modelisation of disaster, after presenting all its definitions. This mathematical modelisation of disaster and also disaster management models allow the researchers to have an idea of different aspects and concepts necessary to save lives.

In Chapter 2, we present our basic implementation of the first alert model based on automated neural network for extracting relevant content from Twitter and Facebook using keywords and hashtags of disaster. This Chapter allows us to begin designing and implementing the heart of the automated learning environment.

The chapetr 3 represents the first enhancement of the automated learning environment: it is based on Deep Learning, namely Feedforward Neural Network, extract, in real time, information on catastrophic events from multiple sources (all the Web) and to immediately alert disaster managers so that they can make quick and efficient decisions that could save lives. Indeed, we propose a new ad hoc real-time alert model for the management of disaster, whether natural or anthropogenic, based on a new multi-view recovery model from multiple sources.

Chapter 4 presents an other improvement of our real-time automated learning environment analysis that is based on a Hybrid of Deep Convolutional LSTM neural network.

Results obtained

To evaluate our proposed model for extracting relevant information through semantically-based learning, we need an annotation for a set of contents. We randomly sampled 1366 messages (*with 547 Facebook content and 819 tweets*) after deleting the duplicates. These messages were observed independently by ourselves [14, 15]. The goal was to identify all relevant content relative to the predefined keywords. This content, manually labeled and cleaned from non-informative information, is used, in this neural network-based automated learning environment, to analyze live new contents through the neural learning. As we want our alert model to be event - independent, it must be able to be used directly on content posted at later events. We therefore adopt the approach of using a set of features for the content extraction task. Since we have a large number of data sets (*14 sets of data*), a few are dedicated to training. Others serve for checking the performance of our proposed model.

In order to show the effectiveness of our model, we examined two specific events, namely the Boumerdes earthquake in May 21^{st}, 2003 and the Algiers flood in November 10^{st}, 2001 - and post-event messages on social networks. Tweets were collected using the Twitter search API and other posts from other social networks, using the Radian6 tool. Both use the search keywords *Boumerdes* and *earthquake* for the earthquake of Boumerdes and the keywords *Algiers* and *flood* for floods of Algiers. Thanks to the Feedforward neural network [16] and after processing the content by removing inconsistencies such as punctuation, special characters, deduplication and replication content [14, 15], we got results confirming the interest to improve this machine learning platform by moving from a simple Autmated Neural Network (ANN) to the Feedforward Neural Network (FFNN) in Deep Learning. This encourages us to move forward in the task of improving it.

In Chapter 4, this Emergency Management Model [69] is designed to support an introductory traineeship in emergency management for citizens, trainees and future disaster managers. Thus, the trainee can use this tool in three modes [16]: Novice, Beginners, and Online manual rehearsal Mode.

Educational messages play a role in improving situational awareness in times of public health emergencies.

Covid-19 pandemic, caused by the coronaVirus SARS-CoV-2, is an emerging infectious disease. Disaster education for the Covid-19 pandemic involves consists of advising to always strengthen preventive hygiene, namely elimination of physical contact, kisses and handshakes, coughing and/or sneezing into the crook of the elbow, using disposable tissues, taking physical/social distancing, wearing a bib, end of gatherings and major events as well as unnecessary trips, promotion of hand washing and avoiding any social or cultural regrouping. But above all, this disaster education consists of constantly rehashing this advice on all information channels, websites and all social media to have as much situational awareness as possible.

This Emergency Management Model [69] is designed to support an introductory traineeship in emergency management for citizens, trainees and future disaster managers. Educational messages play a role in improving situational awareness in times of public health emergencies. Training data is created from the Coronavirus pandemic, Covid-19. This information, easily obtained using the neural network, is annotated manually by volunteers. In order to show the effectiveness of our model, we looked at specific Covid-19 events and post-event posts on several social media: Twitter, Facebook, LinkedIn, Instagram, Google+, Youtube, Messenger, Viber, etc.

All of the experiments reported here were performed on this dataset. With our new model [69] and after cleaning and deduplication, we obtained satisfactory results, above all, after having compared them to the previous models, namely the model based on ANN [14, 15] we had $15,619$, the model based on Feedforward neural network [16] we have $16,942$ and finally the RNN model [89] we have $17,846$.

Our work [69] consists of extracting relevant content not only from Twitter and Facebook, but also from all social media, including, Viber, Instagram, and so on. Thus, our challenge consists of, effectively, filling this lack of information. The present work is relevant for the following reasons. The model used is based on a Convolutional LSTM (ConvLSTM). It recovers in streaming (in real-time, from the social media, contents. Then, it cleans up them with eliminating, before all, non informatifs contents (duplicated and replication contents).

This model integrates encapsulations from multiple sources, and thus retrieves accurate information by combining multiple search results from multiple sources' all the Web). The annotation of the contents obtained by the initial learning is done by volunteers. This Emergency Management Model is also used for smart disaster education by dint of handling it, we discover basic elements of triggering disasters. As it is manipulated, one becomes familiar with certain basic concepts of all disasters. One of the greatest advantages of this model is, above all, used for all types of disasters, whether natural or anthropogenic.

Perspectives

As future works, we believe that our study has explored many potential gaps in disaster management for the future, the main flaw of which is the neglect of the P2P concept.

For pure improvements, we can start with:

1. An improvement can come from the P2P concepts which have to be integrated into Geo-collaborative applications since todayś applications, based on the client / server paradigm (C / S), suffer from major drawbacks such as the need for direct, highly available and reliable communication channels. Indeed, during disasters, naturally representing highly dynamic mobile environments with frequent changes in topology (*network*) and potential disconnections. Due to the large autonomy of the peers involved leading to self-regulation behavior, such networks are very well prepared to address frequent changes in topology [60] such as information and positions. Peers can not only communicate with a server but also exchange information between them. In addition, the scalability feature is related to this by providing support for dynamically joining and leaving nodes and spontaneous networking. Thus, the benefits of applying the P2P paradigm [59] have to be applied to the Geo-Collaboration for Disaster Management as an alternative to the most common Client / Server approaches of GIS and propose to interconnect mobile operators through P2P networks. This P2P network does not require an Internet connection or a telecom service provider network to communicate with others. In addition, the Peer-to-Peer paradigm provides a unique opportunity for service offerings by individual users. Services based on local user proximity can benefit from Peer-to-Peer provisioning without infrastructure support.

2. This work can also be improved by generalizing the application of Peer-to-Peer to mobile environments which offers a number of opportunities and challenges since, originally, Peer-to-Peer was not designed for mobile environments. In addition to well-known file-sharing applications based on Peer-to-Peer networks, new wireless applications are also possible in mobile networks, especially for multi-hop links as in ad-hoc mobile networks.

List of Publications

- International journal with reading committee:

Bouzidi, Z., Amad, M. and Boudries, A., (2019), Intelligent and Real-time Alert Model for Disaster Management based on Information retrieval from Multiple Sources, International Journal of Advanced Media and Communication, Vol. 7, No. 4, pp. 309-330, DOI : 10.1504/$IJAMC$.2019.111193

Bouzidi, Z., Boudries, A. and Amad, M., (2021), Deep LSTM-based Model using Smart Data to Improve Awareness and Education in Marketing, Business Strategy and Financial Forecasting, MC Medical Sciences (MCMS) journal, Volume 1, Issue 5. December 2021, https://doi.org/10.55162/MCMS.2021.01.034, https://themedicon.com/medicalscience 1-issue-5, https://scholar.google.com/citations?view_op=view_citation&hl=en&user=V4F6dhIAA https://doi.org/10.55162/MCMS.2021.01.034

Bouzidi, Z., Boudries, A. & Amad, M., (2021), *Deep Convolutional Neural Network-LSTM-based Model to improve Warning, Situational Awareness and Education in Managing Emergency.* International Journal of Safety and Security Engineering, Vol., No., Month, Year, pp. 1-8, Journal homepage: http://iieta.org/journals/ijsse. Accepted

- International conferences with reading committee:

Bouzidi Z., Boudries A. and Amad M., (2018), A New Efficient Alert Model for Disaster Management, Proceedings of Conference AIAP'2018 : Artificial Intelligence and Its Applications, El-Oued, Algeria

Bouzidi, Z., Boudries, A. & Amad, M. (2020). Towards a Smart Interface-based Automated Learning Environment Through Social Media for Disaster Management and Smart Disaster Education. Advances in Intelligent Systems and Computing. SAI 2020. Vol 1228. Springer, Cham, 443-468. $https://doi.org/10.1007/978-3-030-52249-0\_31$

Bouzidi, Z., Amad, M. and Boudries, A. (2020b), Deep Learning-based Automated Learning Environment using Smart Data to improve Corporate Marketing, Business Strategies, Fraud Detection in Financial Services and Financial Time Series Forecasting. In International Conference on 'Managing Business through Web Analytics - (ICMBWA2020)', Khemis Miliana University, Algeria

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Bouzidi, Z., Boudries, A. and Amad, Mourad, (2021b), LSTM-based automated learning with smart data to improve marketing fraud detection and financial forecasting, 5^{th} International Scientific Conference on Economics and Management, (EMAN 2021), Serbia, DOI:10.31410/EMAN.2021.191

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Bouzidi, Z., Amad, M. and Boudries, A. (2021d), A Survey on Deep Learning in Big Data and its Applications, International Conference on Innovations in Energy Engineering & Cleaner Production IEECP-21, ID : 124, Silicon Valey, California, USA, DOI : 10.6084/$m9.figshare$.14737953

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Abstract

Neural networks-based Alert Model is used to retrieve, in real time, social networks (Twitter and Facebook) contents. Once cleaned of duplicate and replication content, we want to learn, from the first-hand content, thanks to manually tagged information, relevant content to warn and alert people and disaster managers in order to make quick and efficient decisions that will save lives.

Keywords **:** Disaster, Neural learning, Relevant content, Social media.

Résumé

Le modéle d'alerte basé sur les réseaux de neurones est utilisé pour récupérer, en temps réel, les contenus des réseaux sociaux (Twitter et Facebook). Une fois nettoyés des contenus dupliqués et répliqués, nous voulons apprendre, à partir du contenu de première main, grâce à des informations étiquetées manuellement, un contenu pertinent pour avertir et alerter les personnes et les gestionnaires de sinistres afin de prendre des décisions rapides et efficaces qui sauveront des vies. Il est amélioré en environnement d'apprentissage automatisé basé sur Deep Learning pour récupérer de tout le Web. Il est également amélioré pour devenir un hybride d'un ALE basé sur CNN-LSTM profond utilisant la sensibilisation, l'évaluation et l'éducation. Des expériences ont montré qu'il continue à donner de meilleurs résultats que les travaux précédents.

Mots-Clés **:** Catastrophe, Apprentissage neuronal, Contenu pertinent, Média sociaux

مُلَخَّصٌ

نَسْتَخْدِمُ ٱلنَّمُوذَجَ ٱلْمُعْتَمِدَ عَلَىٰ ٱلشَّبَكَاتِ ٱلْعَصَبِيَةِ لِلإِسْتِرْدَادِ مُحْتَوَيْ ٱلشَّبَكَاتِ ٱلْعَصَبِيَةِ (تْوِتِرْ وَ فَيْسْبُكْ) فِي ٱلْوَقْتِ ٱلْفَعَّلِي. بِمُجَرَدِ تَنْظِيْفِ ٱلْمُحْتَوْيِ ٱلْمُكَرَّرِ، نُرِيْدُ آنْ نَتَعَلَّمَ، مِنَ ٱلْمُحْتَوَيْ ٱلْمُبَاشِرِ، اِسْتِنَادًا عَلَيْ ٱلْمَعْلُومَاتِ ٱلَتِيْ تَمَّ وَضْعِ عَلَامَاتٍ عَلَيهَا يَدَوِيًا، وَ ٱلْمُحْتَوَىْ ذِي ٱلْصِلَّةِ لِتَحْذِيرِ وَتَنْبِيهِ ٱلاَشْخَاصِ وَمُدِيرِي ٱلْكَوَارِث مِنْ آجْلِ آتِخَاذِ قَرَارَاتٍ سَرِيعَةٍ وَفَعَاْلَةٍ، مِنْ شَـهَا آنْ تُنْقِذَ ٱلاَرْوَاحِ. تَمَّ تَعَزِيزِ هَذَا ٱلْعَمَلِ، اَوَّلًا وَقَبْلَ كُلِ شَيٍ، مِنْ خِلَالِ تَطْوِيرِ بِيئَةَ تَعَلُّمٍ مُتَمِتَةٍ تَعْتَمِدُ عَلَيْ ٱلْتَعَلُّمِ ٱلْعَمِيقِ لِلْتَعَافِي مِنْ كُلِّ ٱلْوِيبِ وَ ٱلْتَعَلِيمِ ٱلْذَكِي فِي حَالَاتِ ٱلْكَوَارِثِ. ثَانِيًا، يَتِمُّ تَحْسِيْنِ هَذَا ٱلْنَمُوذَجِ مِنْ خِلَالِ دَمْجِ هَجِينِ ٱلْذَاكِرَةِ طَوِيلِ ٱلْمَدَيْ وَطَوِيلِ ٱلْمَدَيْ لِشَبَكَةٍ عَصَبِيَةٍ تَلَافِفِيَةٍ عَمِيقَةٍ مَعَ ٱلْوَعْيِ ٱلْظَرْفِيْ وَتَقْيِيمِ ٱلْكَوَارِثِ وَالْتَعَلِيمِ. اَظْهَرَتْ ٱلْتَجَارُبِ آنَّ يَسْتَمِرَّ فِي ٱلاَدَاءِ بِشَكْلٍ آفْضَلٍ مِنَ ٱلْعَمَلِ ٱلْسَابِقِ.

كَلِمَاتٌ مِفْتَاحِيَةٌ : ٱلْكَوَارِثِ، ٱلْتَعَلُّمِ ٱلْعَصَبِىْ، اَلْمُحْتَوَىْ ٱلْمُرْتَبِطِ، اَلْشَّبَكَاتِ ٱلاِجْتِمَاعِيَةِ