SJSU SAN JOSÉ STATE UNIVERSITY

MTI MINETA TRANSPORTATION INSTITUTE

Technical White Paper: Developing a Community App for Disaster Actions

WP 2254
March 2023

Daniel C. Goodrich, MPA, CEM, MEP, Kaikai Liu, PhD, Zeyu Gao, PhD, Alan Barner, MPA,
Frances L. Edwards, MUP, PhD, CEM

TOPIC: Creating a disaster information app for an individual's smart phone

OBJECTIVE: To create a pathway for creating the disaster information smart phone app

IDEAL READER: Information technology professional interested in merging smart phone application (app) development with artificial intelligence (AI) and big data science to create a real time smart phone app that will display official information about a selected event and social media scrapings for that event, limited by time frame of posting, geo-location of area of interest, and relevance to the specific disaster event selected.

High Level Problem

Community members seek actionable information during disasters to inform their behavior. Official information comes from the government, but people only act when they have verified the government's information by observing the behavior of their acquaintances, an activity known as milling (Wood, et al.,2012). Today milling is generally done by assessing social media posts to sites (Bean, et al.,2015) such as Twitter, Reddit and Periscope. Compounding this problem is a rising mistrust of government entities in twenty-first century America (Pew Research Center, 2020).

High Level Solution

Milling endangers community members by delaying life-saving action as residents review multiple social media sites before deciding to evacuate. One solution to the milling problem would be to create a disaster information app for an individual's smart phone, which would allow the user to view posts in one place, including official information and social media posts about a disaster event in progress, that are time limited, geo fenced and relevant to the disaster selected. This would allow "milling" (Mileti, 2019) to occur within a single app to confirm disaster response actions.

Problems[1]

1. Governments need to disseminate actionable information to the appropriate receivers rapidly during fast moving, dynamic events like wildland urban interface fires (wildfires), floods, hazardous materials events and hurricanes. They do this using traditional print, electronic media, and social media.

1 For detailed information on these problems see Edwards, et al., 2022.

2. Trust in government is at a low ebb, causing many people to question the motives of government agencies, the reliability of their information, and the wisdom of following government information.

3. Community members engage in "milling" after receiving the life safety information from the government. They look to see what their neighbors are doing. They search for more information from the—TV, radio, and social media. They confirm warnings with others. After all of this, they personalize the threat perceptions, and this finally leads to action. However, the milling delays the protective actions by minutes to hours (Mileti, 2019).

4. Lives depend on residents complying with emergency instructions, such as evacuation or shelter in place notices, without spending a lot of time on milling, which could be resolved by a smart phone app that provides both official government information and social media information in one place, allowing for easy comparisons between official instructions and community responses as posted to social media.

5. Social media is filled with unsorted posts from multiple sources, some official, some community-based and some completely unreliable. There are also myriad posts completely unrelated to the disaster that people must sort through to access the information they are looking for. The needed smart phone app has to be able to sort social media messaging to first extract the official posts with life safety information from fire agencies, local governments and other reliable sources. It must then be able to sort social media posts to select just those that are related to the current disaster of interest to the consumer. Those must be further sorted by a specific location of interest to the consumer—home address, work address, child's school and so forth. Finally, the posts must be from a specific time frame that provides actionable information, such as within an hour of the search.

6. Another problem is the need to sort information to create intelligence. This requires a combination of artificial intelligence for sorting and human intelligence for verifying. This will be discussed below.

PATH FORWARD

Solving the Milling and Social Media Problem

When consumers confront the onslaught of information available on social media – official posts, traditional media posts, neighborhood posts, unknown source posts – they are overwhelmed with data. This forces them to develop a personal rubric – a method of making judgements—to engage in sorting the data to create meaning and context for their personal decision making. The rubric has to determine the relevance of the data—is it about an area of interest to the consumer, or about the situation in another county? Is the source trustworthy—an official source, a known source, a neighbor or a completely unknown source? Is the information valid? Does the consumer have the knowledge to judge whether what is being said is physically possible, related to the event of concern, useful to the consumer's decision-making process?

Sense Making

Even more difficult is processing information that is new to consumers, for which they have no orientation. Someone who understands fire behavior will evaluate an evacuation decision from a different perspective than someone without that knowledge. Someone who has lived in the area for a while and has explored the roads will handle evacuation information differently from someone who has never gone out of the neighborhood.

Consumers will be combining and recombining the disjointed social media information to create congruence with their assumptions. This is sometimes known as sense making. “Sense-making refers to how we structure the unknown so as to be able to act on it. …involves coming up with a plausible understanding—a map—of a shifting world; testing this map with others through data collection, action, and conversation; and then refining, or abandoning, the map depending on how credible it is” (Lugtu, 2019, n.p.).

The rubric that consumers use to sort the data will be influenced by what they consider important, and who they consider trustworthy. Consumers who do not trust the police may ignore an evacuation order from law enforcement agencies. Those who distrust social media may ignore a post from an unknown source about the progress of the fire in another neighborhood. The rubric may also allow the consumer to accept all preconceived notions, such as that fire cannot jump a six-lane freeway, and doubt a post that reports on such an event until is it confirmed by a source that has a higher level of trust in their rubric.

In managing public outreach messaging during a disaster, emergency managers may benefit from asking three questions about the social media posts. What is the theory of the event that is coming out of the social media sense making process? What can be inferred from the data that is accepted as valid? What is the time scale for the information? A recent post may offer more current situation analysis, but it may be from an unknown source—such as a resident of that area. By the time that the event is reported by traditional media’s sites, the information may already be stale, or the social media consumer might now be at heightened risk.

Differences between Information and Intelligence

In order to engage in sense making, it is essential to understand the difference between information and intelligence. For the purposes of this paper, the traditional labeling of the sources of information will be changed. Terms such as HUMINT (human intelligence), SIGINT (signals intelligence) and others convolute the difference between intelligence and information. These, and others, are sources of information that contribute to the development of an intelligence product. As such, they will be referred to as “information” to clarify them as a source, and not a product. Human information, for example, comes from collectors’ senses, their acquaintances and their life experiences. Open-source information often comes from traditional and social media sources. Imagery information are photographs and video. There are many other categories of information that can be interpreted/analyzed/exploited to help develop an intelligence product.

All information starts out with different reliability values based on the source of the information, the past experience with the validity of information from that source, and the congruence of that information with information from trusted sources. For example, if a social media post comes from the mayor's office of the city being discussed, many readers will accept that the statements are truthful. If the social media post comes from an unofficial source in a different community, many readers will be skeptical about its veracity and validity. If the National Weather Service issues a warning for a region, and a local public safety official posts a more specific set of instructions for a specific neighborhood, many readers would accept the instructions from the local official. Even though both are trusted sources, the neighborhood-based information will seem more focused on their immediate concerns, while a regional warning might encompass a large area with varying impacts from the expected event.

To turn information into intelligence, emergency managers and community members have to evaluate each piece of information for its value and validity using various techniques. "Information management is the indexing, sorting, and organizing of raw data into files so that the information can be rapidly retrieved" (Iowa, n.d.). Intelligence is verified information that has been interpreted/analyzed/exploited to determine its meaning so it can be used to guide action. Information "analysis and [intelligence] production is the conversion of basic information from all sources into finished intelligence. It includes integrating, evaluating, and analyzing all available data—which is often fragmentary and even contradictory—and preparing intelligence products" (Iowa, n.d.).

OODA Loops

A model for the aforementioned process does exist as a form of shorthand intelligence. Developed by US Air Force Colonel John Boyd to explain the thought process of fighter pilots, they are referred to as "OODA loops" or "Boyd cycles." OODA stands for observation, orientation, decision and action. The general assumption is that these thought processes follow a circular pattern, but in reality, they are far more complex. An explanation of this model is necessary for the reader to grasp its complexity. Starting with observation, the individual takes in information with all of their senses. Interactions with their environment, outside information and unfolding circumstances are taken in (Coram, 2002; Hammond, 2001).

Next is orientation, which functions as a filter. This part is made up of an individual's cultural traditions, genetic heritage, previous professional training and experiences, how they analyze and synthesize information, and how they process new information. Each of these factors interact with each other to create combinations of thought patterns. This is the phase that makes each person truly unique, in that it defines who they are and how they process information. This is why an architect can look at a building and tell if it is structurally sound, or an accountant can detect a spreadsheet irregularity. Their orientation in those particular areas has been honed, just as a mechanic can troubleshoot a car, or a doctor can diagnose a patient. For those who do not have the proper orientation, the observation can lack context and be perplexing. As a result, a loop back to observation from orientation exists to allow newer information for orientation. Someone who lacks the previous experience will cycle through this sub-loop frequently, often slowing down the overall process (Coram, 2002; Hammond, 2001).

Once through the orientation phase, options for possible implementation will present. This is the decision phase, and has sub-loops back to observation and orientation, to enable further feedback. An option is determined, and then the final phase of action occurs. Both a feedback loop through the whole process, and the unfolding integration with the environment, create the need to renew the cycle. If a significant number of the same cycles occur, a form of conditioned reflex, or implied guidance and control, are established. The downside of this system resides in orientation. Without some sort of previous experience, exposure or training, it is quite probable that the period of milling will be extended until an imminent threat is observed, by which time it is too late (Coram, 2002; Hammond, 2001). To this point, the OODA loop has been explained from an individual perspective to enhance a reader's understanding of the process. OODA loops also work in organizations.

When multiple people are exposed to the same information, a common operational picture can develop. Gaps in orientation are sometimes resolved because of the sharing of insights among the group. This collective process can expand the orientation of the participants, and can generate more options for a decision. These options shared among the group loop back through individual observations, further strengthening their orientation to the situation. The net result is an increased probability of a successful decision and appropriate action. Even individuals without any sort of orientation to the situation/information may just follow the group's behavior.

Scholars have noted that the OODA loops approach "focuses on filtering available information, putting it in context and quickly making the most appropriate decision while also understanding that changes can be made as more data becomes available" (Lewis, 2019). Consumers often use a similar strategy for managing emergency information overload, but frequently lack the orientation needed to do it well. Orientation requires placing information into context so that decisions can be made, but consumers often lack the knowledge to give context to their decisions. For example, consumers who do not understand fire behavior may misjudge the level of danger in different potential choices. This lack of orientation makes the decision making less well informed, potentially leading to wrong decisions and actions.

It is also possible for information to be dismissed or ignored through overload. Small distractions can make a person miss details or information that would help them come to a good decision. Just as music or a telephone conversation can distract a driver, causing him to miss cues about road conditions, such as warning signs and road markings, in the midst of an emergency, decision makers may be overwhelmed with information from multiple sources. People absorbing critical information from multiple sources may consciously remove potential distractions to lessen their impact. For example, a driver may turn off the radio when having to navigate a curving mountainous road to aid in their concentration. Emergency operations center staff may limit outside contacts to focus on reliable official information.

The process of turning information into intelligence has many steps.

- Planning and direction are used to define the scope of the resources needed.
- Collection is then employed to bring the various pieces of source information together.
- Processing and exploitation steps focus on reviewing the credibility of the source, the validity of the information, and seek advantage through comparison of the sources.
- Analysis and production steps focus on interpretation of the information through deductive and inductive reasoning, as well as creative, critical and reflective thinking.

The resulting product must be tailored for the end recipient so it can be understood. It is then disseminated to potential users, and the information is integrated into other information to create a usable intelligence product.

Feedback in this process is critical, and the different steps may need to be revisited, when necessary, such as when new information is obtained. Multiple reevaluations may be necessary, depending on the complexity of the information. It is also possible for the entire process to be upended when new information is introduced. Behind all of this is the factor of time. Intelligence products have a limited life span.

Emergency-related events can rapidly generate new information that changes previous understandings of the situation, resulting in the inability to even go through the intelligence cycle. New critical information may have to be evaluated on its own merits and used to create action plans that have new priorities. The factors affecting quality of thought—uncertainty, complexity, bias and subject matter expertise—influence the development of a course of action. Under such circumstances, decision-making is more difficult.

While the intelligence cycle might be compromised under such circumstances, it is not possible to organize the information sources based on the preexisting credibility evaluations. The evaluations, in conjunction with geofencing and time limitation, would function as a validity filter. The net result would be information for the end user to interpret and act on based on their own analysis. This, however, is problematic because it depends on the end user having some knowledge of disaster consequences.

Consideration of collateral impacts in an unfolding disaster is often the first step in determining a course of action. If the fire spreads, will roads be blocked? Will it get so hot that the computer-controlled engine in a car or truck will shut down? Will the fire destroy the cell phone towers and drivers will be left without phone-based guidance systems? The answers to the cascading nature of the event may impact the way that available information is viewed.

Consumers of intelligence products—emergency managers, public safety officials and others—may engage in brainstorming, asking “what will happen”? Their estimation of possibilities is based on their current knowledge and their imaginations. Where might the fire burn? How will wind direction impact the current circumstances? How will changing humidity influence fire behavior? The answers to these questions will be based on the consumer’s personal knowledge and information availability.

Types of Thinking for Social Media Assessment

Consumers will use different ways of thinking about social media as they assess its value in guiding their actions. Inductive reasoning is when a consumer has seen many examples of an event and sees a pattern from it. This pattern recognition leads to a conclusion, which is inductive reasoning. For example, when a consumer watches television news, and sees that in every previous wildfire there has been an evacuation, he concludes that when there is a wildland fire in his area, he will have to evacuate. That is inductive reasoning. Deductive reasoning starts with a general assumption, and tests the logic of the assumption to reach a conclusion. If all wildfires lead to evacuations, and there is a wildfire in her area, she will have to evacuate. Similarly, inductive reason may lead to faulty assumptions, going from a specific observation, to pattern recognition, to a general conclusion (Bhandari, 2022). There is a wildfire on the mountain, and evacuations are usually required in wildfires, therefore an evacuation of my area will be required.

Both types of reasoning can be applied to evaluating the information in social media posts. The problem is that the pattern created by the posts may be based on faulty information, misunderstanding of the situation, or be commenting on a different event that is occurring within the same time period. For example, during the SCU Fire in the Bay Area in 2020, people living in Stanislaus County on the eastern side of the Diablo Mountains were posting information on social media about progress of the SCU fire and evacuation in their county. People in the City of San Jose read the information and used deductive reasoning to conclude that they also needed to evacuate, even though they were on the western side of the Diablo Range and the fire was burning mostly on the eastern side of the mountain. Therefore, the pattern was not applicable because evacuation only occurs in areas where fire is approaching.

People also use creative thinking about social media posts to evaluate their safety. Creative thinking is looking at a problem and developing alternate ways to solve or cope with the problem. If a resident who needs to evacuate looks at fire department routing instructions, then looks at Waze and sees that the prescribed route is crowded with traffic, he may decide to take a different route to evacuate. While this may be good deductive reasoning—if the route is crowded, I will go a different way—his alternative needs to be carefully tested through reliable website information about what roads are open to the public, such as Caltrans's website for current road conditions. Milling using social media can lead to discovering posts from others who have taken alternative routes, but whose information may be hours old. The alternate route may now be in the path of the fire, or be blocked by fire apparatus. The poster of the information may also have a different perspective on what is a usable route—driving a 4x4 truck versus the social media user's Prius.

Critical thinking relies on careful observation of facts, estimation of the validity of those facts—is the source reliable?—and then interpreting the facts in this situation (Ennis, 2010). These steps lead to the ability to solve a problem, make a decision and communicate this thought process clearly to others. In the example of information from Stanislaus County, a critical thinker would consider the location of the source of the post, the length of time since the post was made, and information about the person posting the message to determine whether the post was relevant to the problem that needs to be solved—should I evacuate? Recognizing that the post was from the eastern slope of the mountain, and that the fire would have to burn uphill to the summit and then downhill to San Jose, the critical thinker would confirm the fire's location on the Cal Fire website, and judge that evacuation would not be needed yet.

Intelligence is information that has been analyzed—subjected to inductive and deductive reasoning, and to creative and critical thinking. To make information useful to an emergency manager or community member, the intelligence product has to be tailored to the consumer's specific needs. While large amounts of data can be scraped from social media posts, a sorting, evaluation and analysis process is essential before the collected data becomes intelligence.

Some of the sorting can be done using technology to ensure that the information is timely and relevant to the reader. Artificial intelligence, geotags and time stamps can all contribute to the intelligence creation process. For example, during the SCU fire, useful information for people in the City of San Jose would be most likely to come from the western slope of the Diablo Range, on the same side of the mountain as the city. This sort can be done using geolocation tags embedded in the post. Due to the dynamic nature of fire, the most useful information would come from recent posts. This sort can be done using time stamps. Is the source of the information reliable? A collection of identifiers can be used to sort messages from official government sources like Cal Fire, San Jose city departments, and Santa Clara County resources.

To address possible distrust of government, the intelligence product should include information from widely trusted organizations like the American Red Cross, Catholic Charities and similar community organizations. Posts from the social media site Nextdoor might also be included for the neighborhood of the consumer using geolocation. The issue for the end user is the reliability of the information source from their perspective, not the programmer's. This implies a need to allow tailoring of the potential sources in the application by the end user, or risk dismissal of the application.

An App to Sort Information

To merge the information and create a set of results sorted by relevance (time and location), an application needs to be created that would allow a user to set some parameters and obtain information sorted for probable usefulness. Currently, social media streams information that may come from distant communities, and that may have been created days ago and recently re-posted. An app would become a decision-making tool for emergency managers or community members. With such a sorting application, consumers are now presented with a partially tailored intelligence product, but they have to apply critical thinking skills to determine which posts are useful for creating answers to their current questions, such as should we begin to move the cattle further down the slope? Should we let the horses loose to run from the fire? Should we just pack the car, or should I actually move the family into a motel away from the mountain?

The end users may dismiss the result of the automated sorting process because it goes against their preconceived notions, orientation or for some other reason "does not fit," or the information is inadequate. While the sorting processes can be accomplished by functions using big data and artificial intelligence, the final analysis relies on human intelligence. Even the largest social media organizations cannot rely entirely on machine learning to evaluate safety issues. As discussed in the main report (Edwards, et al., 2022), in the Social Media and Situational Awareness section, in social media organizations like Facebook, human analysts review all the screened messages and apply critical thinking to determine the value of the information, and the actions that should result from it.

The same problem exists for people creating AI to manage the enormous amounts of information that originate in social media posts. The OODA Loop model, which has been adopted by many tech companies, can provide a template for machine learning to "identify potential outcomes" from the posted information (Lewis, 2019), leading to grounds for decision making. Still, the end user will need to interpret the potential outcomes, and determine whether the recommended course of action is appropriate or not. As noted by several incidents of people blindly following their GPS while driving (Trimarchi, n.d; Edmunds, n.d., Hansen, 2015), technology does not always know best. Further, personal injury law findings are currently making it possible for accident victims to hold GPS makers responsible for their negligence in the design of the guidance system (Kaplan, n.d.). Considering this case precedence, it seems likely that similar lawsuits could result from an application that provided a sub-optimal solution to a situation that is rapidly developing. A disclaimer is therefore recommended, with a reminder that the end user is ultimately responsible for any action or inaction. Those designing the evaluation algorithm for social media sorting will have to use a similar set of steps for the big data and AI functions.

Solving the App Problem: Creating a Smart Phone App

Smart phones have the potential to become the most effective platform to deliver important information during disaster events. Social media applications on smart phones, like Twitter, are ideal platforms for real-time delivery of news, but lack some important features to become a good emergency notification application. The most important challenge is determining which news is relevant to the user and whether it should be considered an emergency or not. This project proposes an intelligent emergency notification application that performs data mining automatically from online social media platforms, applies a smart filter to filter out non-emergency and unrelated news, and delivers only classified emergency notifications to users. Instead of using multiple separate systems or models to achieve the goals, researchers propose a joint Multiclass Text Classification model to filter out non-emergency Tweets, and classify the type of emergencies in one end-to-end neural network model. Researchers would further train a Named Entity Recognition (NER) model to extract locations from the classified emergency news. Researchers have evaluated this system in multiple historical emergency events and demonstrated the effectiveness and latency of emergency news delivery in various performance metrics.

As shown in Figure 1, the overall application design is divided into four different components, based on their functionalities and roles. The “Pull Server” is responsible for monitoring Tweet streams to listen for any new Tweet post. In the event of detecting a newly posted Tweet, the Tweet, along with its metadata, will be sent to the “Analysis Server”. The “Analysis Server” is responsible for processing and classifying all received Tweets. It classifies whether each received Tweet is related to an actual disaster incident or not, and, if it is, classifies it to one of the listed disaster types. It will also extract all the locations mentioned in the text. If the received Tweet is related to an actual disaster incident, its information will be sent to the Notification Server via HTTP request. The Notification Server is responsible for sending out push notifications to all users subscribed to matching disaster types and matching locations. The frontend application is responsible for receiving notifications and providing interface like setting subscriptions or viewing disasters to users.

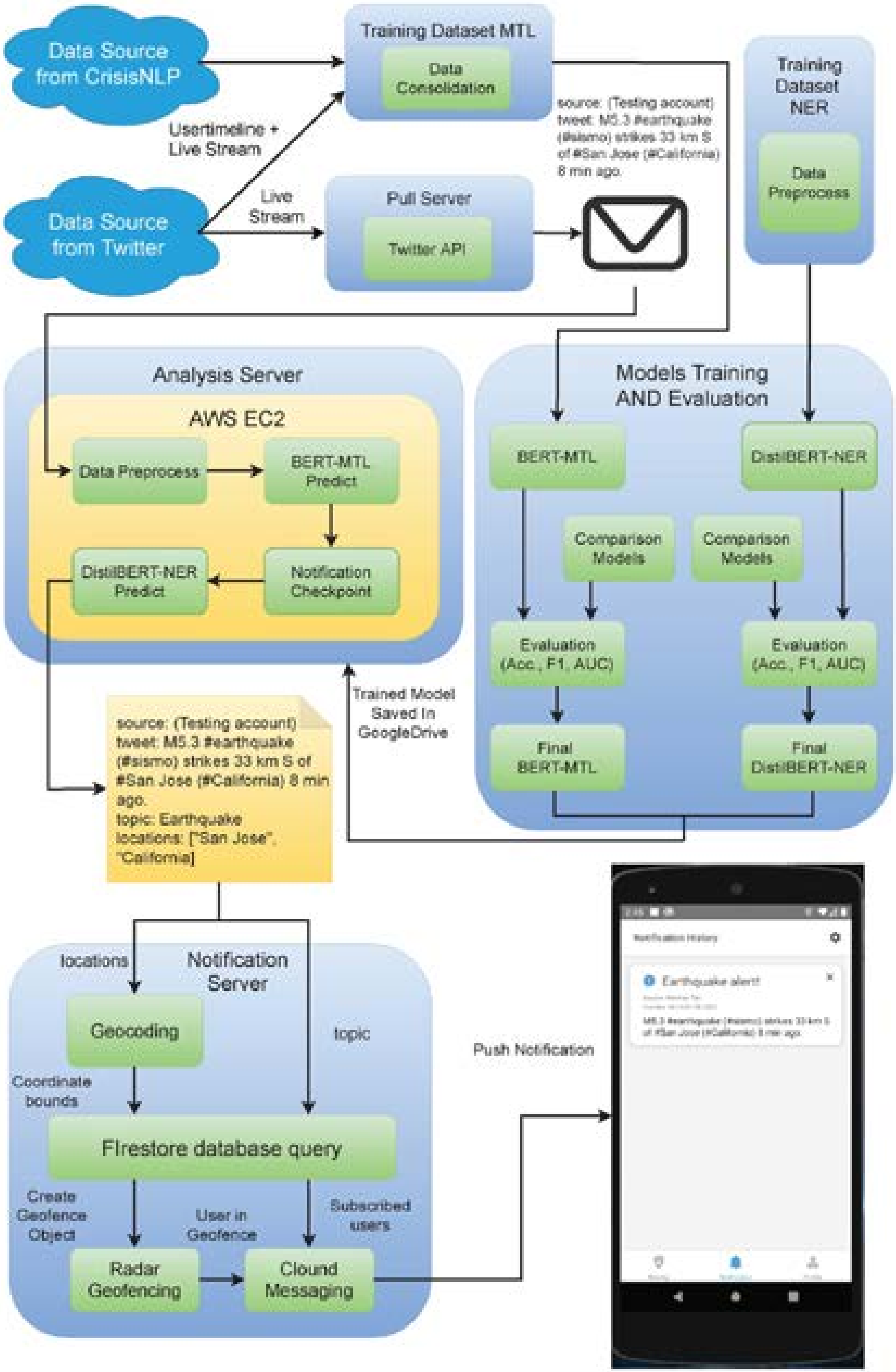


Figure 1. Project Architecture

Proposed BERT-MTL Model

The “Analysis Server” has two text classification goals: 1) classify the news as emergency, and 2) classify the emergency category. Instead of using multiple separate systems or models, researchers propose a joint Multiclass Text Classification model to perform end-to-end classification tasks with low-latency and low computational cost. Based on the BERT model, we propose one **BERT-MTL** with two classification task headers and a pre-trained BERT model from the Tensorflow-Hub as the backbone. As shown in Figure 2, the BERT backbone has been pre-trained for English on the Wikipedia and BookCorpus, and it has 12 hidden layers, 12 self-attention heads, and hidden size of 768.

Two tasks share the same BERT layer and a hidden layer that is connected to the output of the BERT layer. The hidden layer has 64 neurons. Pooled output of the BERT layer is used as the inputs of the hidden layer, so a full sentence receives its embedding. Pooled output is used for classification task in most situations. Then, two sets of a dense layer and a dropout layer with dropout rate of 0.2 are used for two different classification tasks. The first set is for classification of disaster notification or not, and the second set is for classification of disaster categories. The first task is a binary classification that determines whether the tweet is about notification of disaster, so sigmoid and binary cross-entropy is used for activation function and loss function. The second task is a multi-class classification that identifies the category of disasters, so softmax and categorical cross-entropy is used as the activation function and loss function.

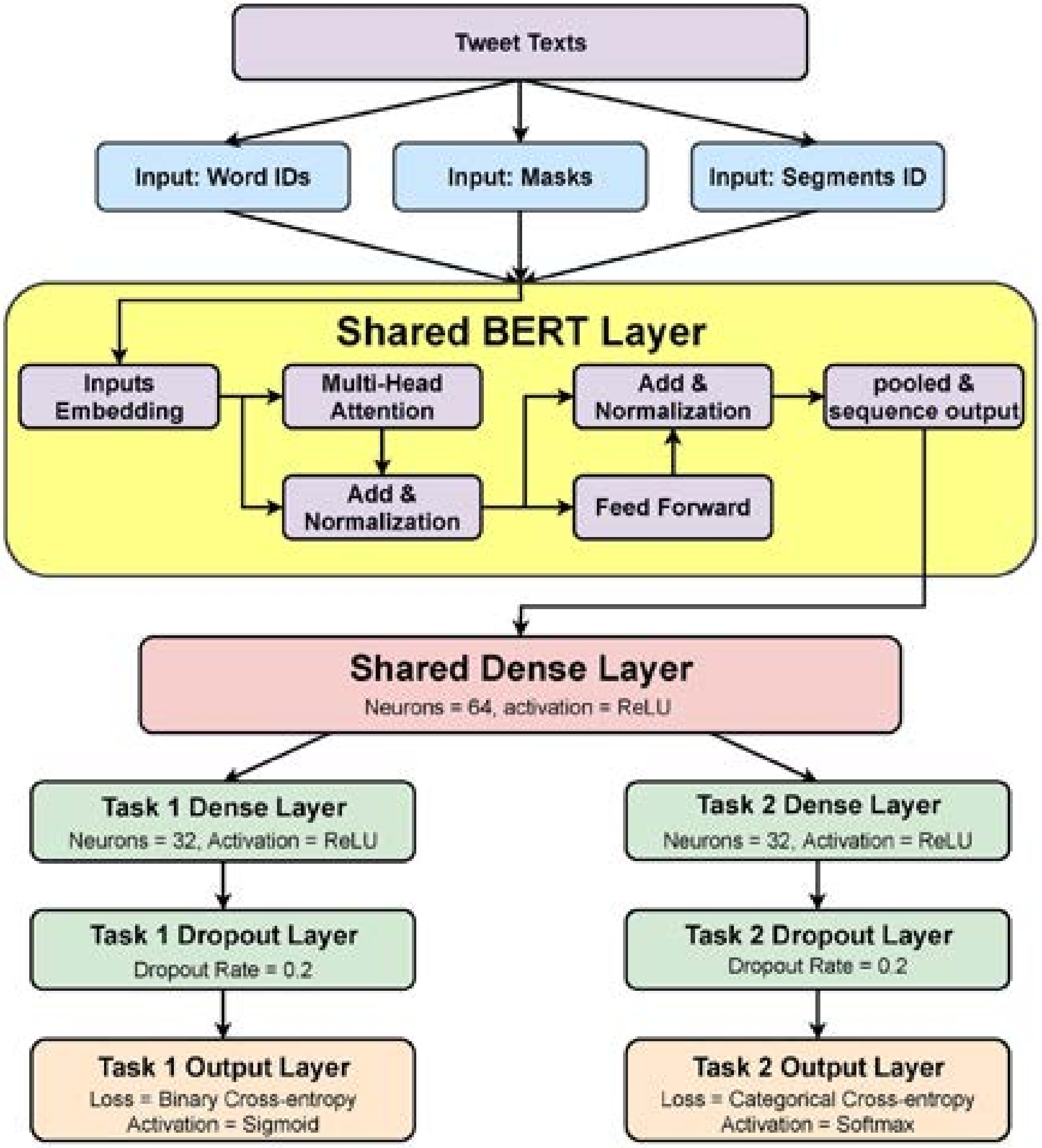


Figure 2. BERT-MTL

Figure 3 shows some user interface of the developed mobile app, including the topic subscription, location setting, user profile, incident details, and emergency notification alert.

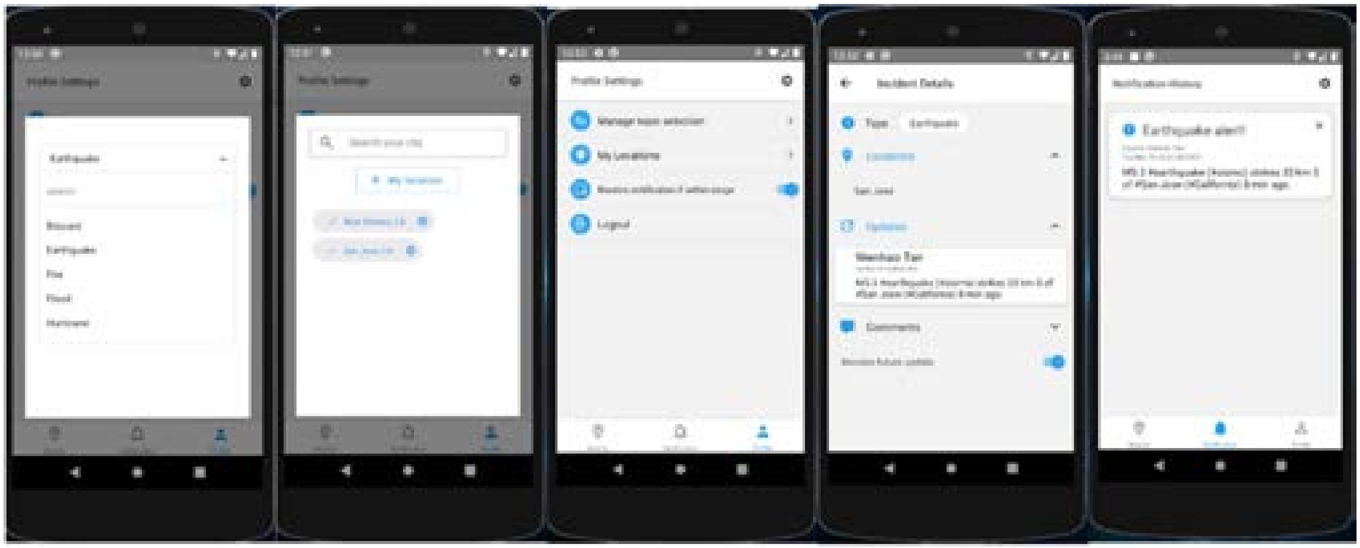


Figure 3. Mobile Application Interface

Solving the Sorting Problem with AI and Big Data: Emergency Big Data and AI Solutions

The Current Status of Emergency Information Alerting

Today, diverse emergency alert messages are generated by a number of government agencies, including Federal Emergency Management Agency (FEMA) (n.d.), US Geological Survey (USGS), National Oceanic and Atmospheric Administration (NOAA) (2005), Wildland Fire Interagency Geospatial Services (WFIGS), Emergency Alerting System (EAS), and Wireless Emergency Alerts (WEA). These alerts are posted and distributed over wireless internet to selected emergency mobile apps, social medial network applications (such as Twitter, Facebook), and public media channels, such as TV, radio, and emergency speakers (PiHa & Yu, 2017). Most of these emergency mobile apps allow their clients to respond to their received alerts by posting their observations and status comments (Menon & Kala, 2017).

Emergency Mobile Apps

Up to now, there are a number of major emergency mobile apps which generate and post different types of emergency alerts relating to different natural disasters. Table 1 shows the detailed comparison.

Table 1. A Comparison of Emergency Mobile Apps for Emergency Alerts

Disaster Type	Fema	Emergency-American red Cross	ReadySCC	DisasterAlert	MyShake	Fireguard	PulsePoint Respond	FWAC	Wildfire Info	Wildfire Alert	Android Earthquake Alerts
Earthquake	Yes	Yes	Yes	Yes	Yes	No	Yes	No	No	No	Yes
Wildfires	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No
Bioterrorism	Yes	Yes	No	Yes	No	No	No	No	No	No	No
Floods	Yes	Yes	Yes	Yes	No	No	Yes	No	No	No	No
Pandemics	Yes	Yes	No	Yes	No	No	No	No	No	No	No
Home Fires	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	No
Chemical	Yes	Yes	Yes	No	No	No	Yes	No	No	No	No
Explosions	Yes	No	Yes	No	No	No	Yes	No	No	No	No
Extreme heat	Yes	Yes	No	Yes	No	No	No	No	No	No	No
Tsunamis	Yes	Yes	Yes	Yes	No	No	Yes	No	No	No	No
Power Outage	Yes	Yes	No	No	No	No	No	No	No	No	No

Basic Info	Fema	Emergency-American red Cross	ReadySCC	Disaster Alert	MyShake	Fireguard	PulsePoint Respond	FWAC	Wildfire Info	Wildfire Alert	Android Earthquake Alerts
Google PlayStore	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Apple AppStore	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No
Owner	USA Govt	Red Cross	County of Santa Clara	PDC Global	UC Berkeley	Global App Solutions	Workday Foundation	True North Gear	David Gross	WildfireAlert LLC	Google
Source of alert	NWS	NWS, NOAA, USGS, FEMA	FEMA, Department of Homeland Security	SmartTM technology	USGS	NASA Fire Information system	911	USGS, WFAS	WFIGS, IRWIN	USGS, WFAS	USGS
Language Support	2	2	2	11	2	1	1	1	1	1	1

The reliable sources of information about wildfires are USGS, Wildland Fire Assessment System (WFAS), National Weather Service (NWS), FEMA, Department of Homeland Security (DHS), WFIGS, National Aeronautics and Space Administration (NASA) fire information system, 911, Integrated Reporting of Wildland Fire Information (IRWIN), NOAA, and SmartTM technology (Hartman & Ashrafi, 2004).

Social Media Network Apps for Emergency Alerting

In addition to major emergency mobile apps, social media network applications are used as another effective mean to post diverse emergency alerts. Table 2 shows the major players in social media network apps which support posting and distribution of diverse message alerts to the public. Moreover, Table 2 also shows the detailed comparison of these social media apps in posting diverse types of emergency alerts, information sources, and language support.

Table 2. Social Media Apps for Emergency Message Alerting

Basic Info	Facebook	Twitter	Instagram	WhatsApp	WeChat	LinkedIn	nextdoor	Line
Earthquake	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Wildfires	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Bioterrorism	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Floods	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Pandemics	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Home Fires	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Chemical	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Explosions	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Extreme heat	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Tsunamis	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Power Outage	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Google PlayStore	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Apple AppStore	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Owner	Mark Zuckerberg	Jack Dorsey, Noah Glass, Biz Stone, and Evan Williams	Kevin Systrom	Brian Acton and Jan Koum	Allen Zhang	Reid Hoffman	Nirav Tolia, Sarah Leary, Prakash Janakiraman and David Wiesen	Naver Corp
Source of alert	NWS, NOAA, USGS, FEMA, WFAS, WFIGS, IRWIN	NWS, NOAA, USGS, FEMA, WFAS, WFIGS, IRWIN	NWS, NOAA, USGS, FEMA, WFAS, WFIGS, IRWIN	Users	Public Agencies, users	NWS, NOAA, USGS, FEMA, WFAS, WFIGS, IRWIN	Public Agencies, Firefighters, Users	Public Agencies, users
Language Support	43	34	36	40	20	24	13	17

Although the information data points contained in social media applications are similar to each other, there are great differences in the information organization and presentation between them. According to our recent survey, the data presented in social media applications are structural and relevant. Table 3 shows a detailed comparison of emergency information contents in structures.

Table 3. A Comparison of Emergency Message Structures of Different Social Media Apps

Features			Facebook	Twitter	Instagram	WhatsApp	WeChat	LinkedIn	nextdoor	Line
Notifications	Alerts	Advanced	Yes	Yes	No	No	No	No	No	No
		Realtime	yes	Yes	Yes	No	Yes	Yes	Yes	Yes
	Sharing & Accessibility	Text	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Email	yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Social Media	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		T.V	Yes	Yes	Yes	No	No	No	No	No
		Radio	No	No	No	No	No	No	No	No
Post	Who Can Post	Users	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Authorities	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Type		Detailed Info	Detailed Info	Detailed Info	Detailed Info	Detailed Info	Detailed Info	Detailed Info	Detailed Info
	Visibility	Followers	Yes	Yes	Yes	NA	Yes	Yes	Yes	Yes
		Other Users	No	No	No	Shared Contacts	Shared Contacts	No	Yes	Yes
		Authorities	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Who Authorize Posting		Users & Authorities	Users & Authorities	Users & Authorities	Users & Authorities	Users & Authorities	Users & Authorities	Users & Authorities	Users & Authorities
Preparation & Safety Tips	Before Disaster		Yes	Yes	Yes	No	Yes	Yes	Yes	No
	During Disaster		Yes	Yes	Yes	No	Yes	Yes	Yes	No
	After Disaster		Yes	Yes	Yes	No	Yes	Yes	Yes	No
	Build a kit		Yes	Yes	Yes	No	Yes	Yes	Yes	No
Sheltering	Disaster Recovery Centers		Users & Authorities	Users & Authorities	Users share	Users share	Users & Authorities	Users & Authorities	Users share	Users share
	Emergency shelters		Users & Authorities	Users & Authorities	Users share	Users share	Users & Authorities	Users & Authorities	Users & Authorities	Users share
	Hospital		Users & Authorities	Users & Authorities	Users share	Users share	Users & Authorities	Users & Authorities	Users & Authorities	Users share
	Food		Users & Authorities	Users & Authorities	Users share	Users share	Users & Authorities	Users & Authorities	Users & Authorities	Users share
	Own emergency meeting place with family		Users share	Users share	Users share	Users share	Users share	Users share	Users share	Users share

Current Emergency Alert Message Distribution Infrastructure

Figure 4 shows the current emergency alert message distribution infrastructure based on the internet and wireless internets. It has the following special features:

Multi-party alert generation—Emergency alerts usually are generated by a number of dedicated government agencies. However, no real-time alert updates are provided dynamically to the general public and the city emergency office.

Distributed posting and distribution—Alert messages are posted and distributed by different agencies without a central control solution in alert distribution, and tracking, and management, and monitoring. There is a lack of a clear picture about message alert distribution, reachability, and coverage status.

Crowd-sourced alert responding from the public—Most emergency mobile apps and social media network apps allow their clients (the general public) to respond to their received alerts and share their comments or observations in an ad-hoc manner, using a crowd-sourced mode. Due to the lack of an effective alert response validation mechanism in the city of emergency office and government agencies, these shared alert responses from the general public on emergency mobile apps and social media networks cause a great deal of confusion and inconsistent alert messages to the consumers and emergency response teams (such as police and fire fighters).

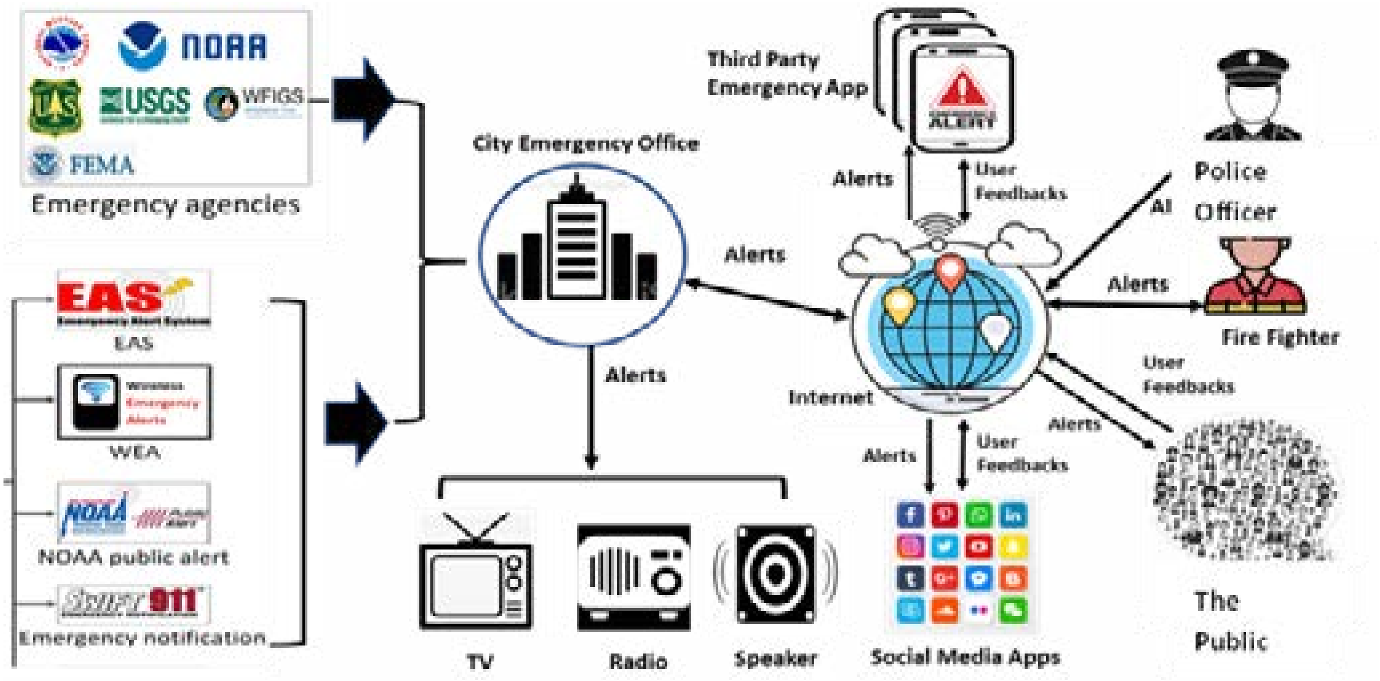


Figure 4. Current Emergency Message Distribution Infrastructure

There are a number of major problems in current emergency alert message distribution infrastructure. While public information officers (PIOs) in emergency operations centers (EOCs) may be able to issue well-developed emergency response guidance to the public, the community members post unregulated and unvalidated information to social media. Other community members engage in milling (Mileti, 2019), reading diverse posts to develop a plan of action, influenced by social media misinformation as well as by official validated information.

Problem #1: Lack of real-time updates of posted emergency alerts

– Diverse emergency alerts are generated and posted by multiple government agencies from various jurisdictions, without real-time updates on a real-time emergency message alert and tracking platform. Cross county communication does not exist. It is very difficult for a city emergency office to provide consumers with a complete dynamic picture (or snapshot) about current active alerts involving multiple jurisdictions, or for the office to follow and understand the dynamic status of posted active alerts from community members.

Problem #2: Lack of reliable and effective alert response message validation across jurisdictions

– Emergency messaging is issued from a variety of organizations, including transportation, special districts, public safety and others, which are not always coordinated. This has caused inconsistent emergency alerts and updates due to the lack of a well-defined AI-powered emergency response validation solution to collect, process, analyze, and validate diverse emergency responses from various emergency mobile apps and social media network applications.

Problem #3: Lack of well-defined standards for emergency response templates and protocols

– Current emergency mobile apps and social network applications provide their proprietary ways to allow clients to respond to their received emergency alerts in an ad-hoc response format without a consistent user interaction approach. Meanwhile, it has no well-defined standards for interaction APIs (or message protocols) among diverse emergency mobile apps, social media networks, and city emergency offices, as well as government agencies.

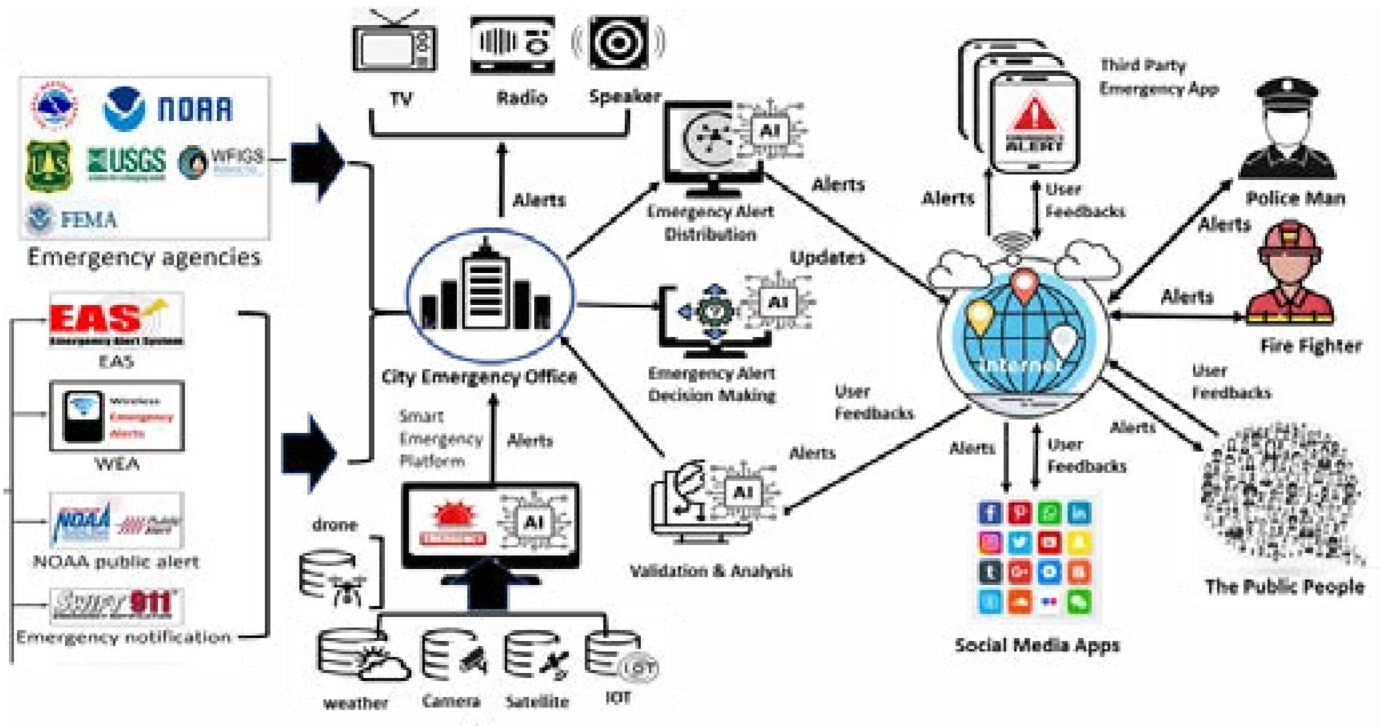


Figure 5. Data-Driven AI-Powered Emergency Message Distribution and Infrastructure

Clearly, there are several urgent needs to address these problems.

Need #1 – Building a real-time intelligent emergency detection and alerting platform based on diverse big data and machine learning models to provide dynamic emergency detection, classification, and progression prediction with real-time alerts and updates to the city and the consumers. As shown in Figure 5.

Need #2 – Building an intelligent emergency alert message management platform for the city emergency management office to control and manage diverse emergency alerts and updates in message receiving, posting, and distribution.

Need #3 – Building an AI-powered emergency message response validation solution. Its major purpose is to use intelligence-based text analysis and classification models and techniques to validate diverse received emergency response messages posted by the public in various emergency mobile apps and social media network applications. The objective of this solution is to carry out intelligence-based response processing and classification, and conduct dynamic response validation based on message accuracy, reliability, trustworthiness, consistency, and similarity.

Emergency Big Data and Classifications

Emergency Message Big Data

To address the problems discussed above, different types of emergency messages and responses from different emergency mobile apps and social media apps need to be collected, processed, validated, and tracked in large-scale as big data. Most of these emergency data are formatted as text messages only. Some of the alerts and alert responses are rich media text messages with photo images, resulting in a variety of emergency big data, as discussed below.

Emergency Mobile App Data

During natural disasters, mobile applications have been widely used as a tool for direct emergency alert posting, responding, and rescue operations (Huang & Guo, 2020). A number of government agencies created dedicated emergency mobile apps as a broadcasting tool to send and distribute diverse emergency alerts and warnings for public safety events. At the same time, the public could post their responses and discussions related to current posted emergency alerts. These emergency mobile apps are developed by different government agencies for posting specific emergency alerts. As a result, there is a lack of a centralized one-stop place for the public to find all of the emergency alerts and updates. As discussed above, there is an urgent need to provide a centralized emergency alert management platform which supports: a) real-time emergency collection of diverse posted emergency alerts from different mobile apps, b) real-time distribution to other mobile apps and social network apps, and c) effective tracking and monitor of alert posting and delivery, as shown in Figure 6.

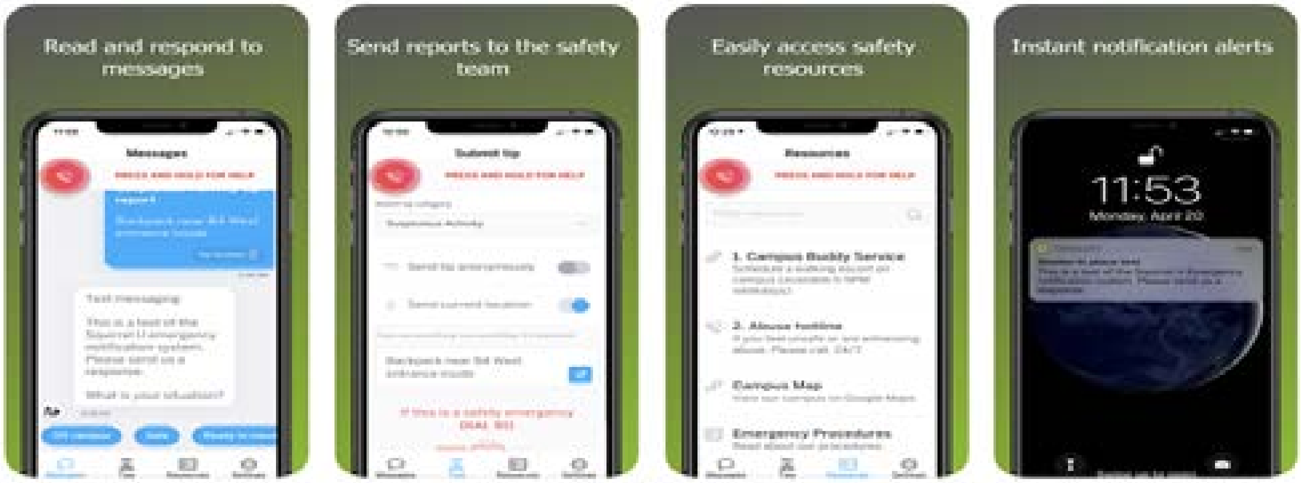


Figure 6. Mobile Application Data about Emergency

Emergency Data from Social Media Network Apps

Social network apps provide another effective tool to post and distribute emergency alerts and responses among consumers and city emergency offices (Amin, 2020). These social network applications generate large-scale social media alerts and response messages on the Internet because most social network apps support message sharing and crowd-source response posting by the public. These real-time alert messages frequently cause problems for the public and local city emergency offices to understand real-time emergency status and alert updates because of the lack of authorized and intelligent message validation. As pointed out above, emergency alerts and response messages generated by social network apps must be considered and processed as social media big data that need to be collected, processed and classified, tracked and monitored, and validated based on AI-powered solutions and techniques (Rudisill, 2011). Figure 7 provides one example about flooding on the floor of the New York Stock Exchange (NYSE). Today, many social media apps allow clients to add photo images, audio clips, and videos with their text messages. This leads to certain complexity in message processing, classification, and recognition for diverse alerts.

Figure 7. A Social Media Emergency Data Sample on a Social Network Application

IOT Sensor and Camera Data

Today, many smart city projects have setup dedicated IOT sensors and camera stations on selected streets and city community areas to support the surveillance needs in crime watch, emergency alerting, local traffic monitoring, and city community monitoring (Bicans, Kviesis,& Avotins, 2019). To effectively support city emergency alerts and responses, these IOT and camera data must be collected, classified, and stored in a city emergency cloud platform and big data center. Most IOT sensors generate structured sensor data. Figure 8 shows some sample IOT sensors for a local city. Unlike IOT sensors, some surveillance stations for smart cities have installed stations in city communities with camera, microphones, IOT sensors, and speakers. These smart city IOT stations generate useful rich media data (such as images, audio, and video data) for real-time emergency detection and validation based on AI-powered solutions.

Figure 8. IOT Sensor and Camera Data- Weather

Historical Emergency Data

Historical data of diverse emergency events and big data resources about a city are essential for learning and building AI-powered solutions to address different types of location-specific emergency events/alerts from diverse natural disasters (Carlton, 2006). Analysis of historical emergency data could help us to understand and analyze the causes, progressions, and consequences of emergency events in affected areas. Moreover, these data could be very useful to prepare a training dataset for developing AI-powered solutions and models. Table 4 shows a collected sample of Wildfire History Data from the California Department of Forestry and Fire Protection. Similar emergency historical data could be collected from different sources for other nature disasters, including wildfires, dust storms, floods, hurricanes, tornadoes, volcanic eruptions, earthquakes, tsunamis, and winter storms.

Table 4. Wildfire History Data Sample

Column Name	Description	Range	Unit
Year	Year of Fire occurred.	(2016, 2018)	year
State	State where the fire occurred	'CA'	NA
Fire_Name	Name of the fire	NA	NA
Alarm_Date	Alarm date of the Fire.	(01/01/2016 ,12/31/2018)	NA
Cont_Date	Containment date for fire.	(01/01/2016 ,12/31/2018)	NA
Cause	Reason for the fire.	(1,19)	NA
Report_Ac	Area Consumed in the fire	(0, 25)	acre
GIS_Acres	Area Calculated by GIS	(8.266294, 26.002495)	acre
C_Method	Collection of data method coding	(1, 1)	NA
Objective	Suppression or resource benefit	(1,1)	NA
Fire_Num	Number assigned to the fire	(00001890 1716, 00000825)	NA
Shape_Length	Length of the area burnt	(9.093210, 445282.444798)	meter
Shape_Area	Area burnt	(6.130331,1.660030e +09)	Square meter
Geometry	Shape of the area burnt	Within study area	degrees

** Source - https://frap.fire.ca.gov/frap-projects/fireperimeters/*

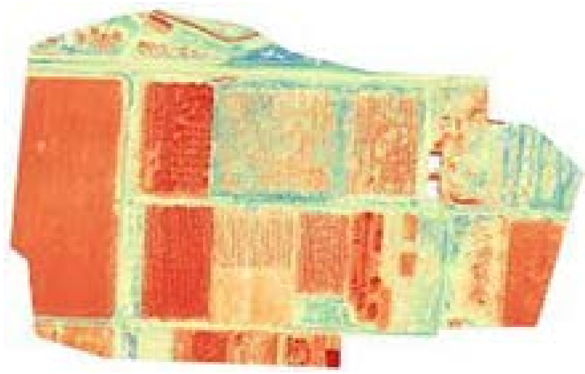
Drone and UAV Big Data

To effectively understand and detect emergency events and natural disasters, many researchers have started to use other types of big data as resources to develop data-driven machine learning models to support real-time risk analysis, detection, classification, and prediction of diverse natural disasters and emergency events, and generate real-time emergency alerts and updates based on intelligent forecasts. Data collected from drones or UAVs is one of these resources.

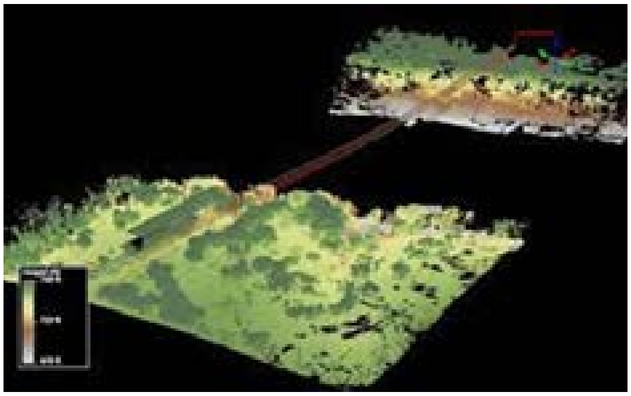
In recent years, UAV technology has developed rapidly and played an important role in emergency risk analysis and prevention, response and rescue operations (Kwan, 2021). Since drones and UAV have the advantages of flexibility, simple operation, suitability for operation in complex environments, and being less limited by traffic conditions, they can be used to help an emergency communications center to grasp the on-site situation at the time and support the emergency rescue work and task forces. At the same time, UAV plays an important role in emergent site data collection and analysis.

They also can assist emergency search and rescue, airdrop of materials, and air communication relay by loading infrared thermal imaging, lidar and emergency communications (Trepekli, et al., 2020). It has unique advantages and broad application prospects in flood control and drought relief, geological disasters, forest fire prevention and fire extinguishing, earthquake disaster emergency rescue and other disasters. Figure 9 provides examples of some of these technologies.

a) Drone Mapping Aerial Imagery Example



b) Drone LIDAR Data Sample



c)Drone Camera Data Sample

d) Drone Infrared Data

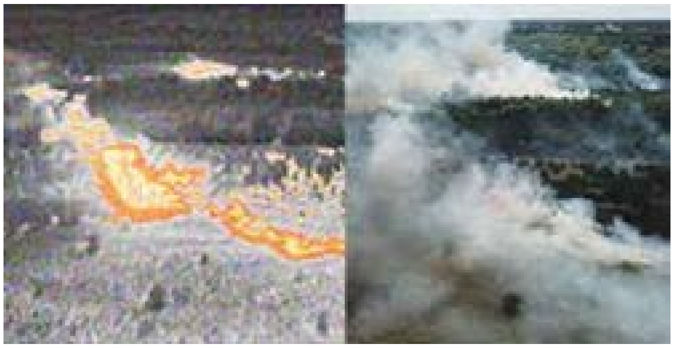


Figure 9. Drone Collected Data Samples

Figure 9 shows four types of data collected from drones or UAVs:

- Drone mapping aerial images, which usually are collected by a drone (with a data collection camera) based on a pre-defined flying path. The collected images will be processed to form the desirable 2D mapping images.

- Drone LIDAR data that is generated by a LIDAR sensor on a drone. Unlike a camera-based drone mapping image, drone LIDAR data could be used to generate 3D information on a targeted site.

- Drone camera-based images (or video), which are collected for monitoring and surveillance of on-going emergency events/alerts.

- Drone infrared data, that is useful to check and monitor wildfire activities and progression.

Satellite and Remote Sensing Data

Remote sensing is the process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance (typically from satellite or aircraft). Special cameras collect remotely sensed images, which help researchers “sense” things about the Earth. NASA observes Earth and other planetary bodies using sensors aboard satellites and aircraft that detect and record reflected or emitted energy (Hall & Ward, 2021). Remote sensors, which provide a global perspective and a wealth of data about Earth systems, enable data-informed decision making based on the current and future state of the planet.

Table 5 lists the number of satellites that provide free image datasets useful in emergency monitoring and tracking of diverse disasters. Recently, many researchers have used different satellite images and remote sensing data to train and develop machine learning models and solutions to support dynamic detection and classification, risk analysis and prediction of specific disasters, such as wildfires and floods.

Table 5. Different Satellites

NAME	Resolution	Frequency	Launch Date	ORBIT
GOES-16	2 km	5 min	2017	Geostationary
GOES-17	2 km	5 min	2019	Geostationary
Aqua-MODIS	250m - 1 km	daily	2002	Polar
Terra-MODIS	250m - 1 km	daily	1999	Polar
SuomiNPP-VIIRS	375 m	12 hr	2011	Polar
NOAA20-VIIRS	375 m	12 hr	2017	Polar
Landsat 8	30 m/ 15 m	16 days	2013	Polar
Sentinel 2	10, 20, 60 m	10 days	2015/2017	Polar

The images collected by remote cameras on satellites are known as satellite image data. Cameras installed on satellites could usefully look and monitor the large areas on the Earth’s surface. This allows observers to see much more than can be seen when standing on the ground. In addition, cameras on satellites can be used to make images of temperature changes in the oceans. Some specific uses of remotely sensed images of the Earth include:

- Wildfire detection, monitoring, and tracking, as well as burning area analysis
- Volcano and dust storm activity monitoring and tracking
- Flood detection, monitoring, and tracking, as well as flooding area analysis
- Cloud tracking to help predict the weather
- Tracking the growth of a city and changes in farmland or forests over several years or decades.

Figure 10 shows three satellite image samples generated from three different satellites: GOES17, MODIS, and Landsat 8.

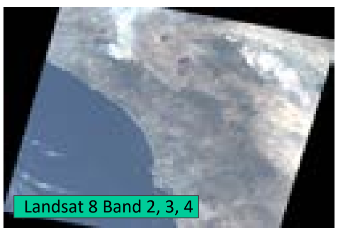


Figure 10. Wildfire Satellite Images from GOES17 and MODIS

Figure 11 shows flood satellite images from Landsat and Sentinel-2 satellites.

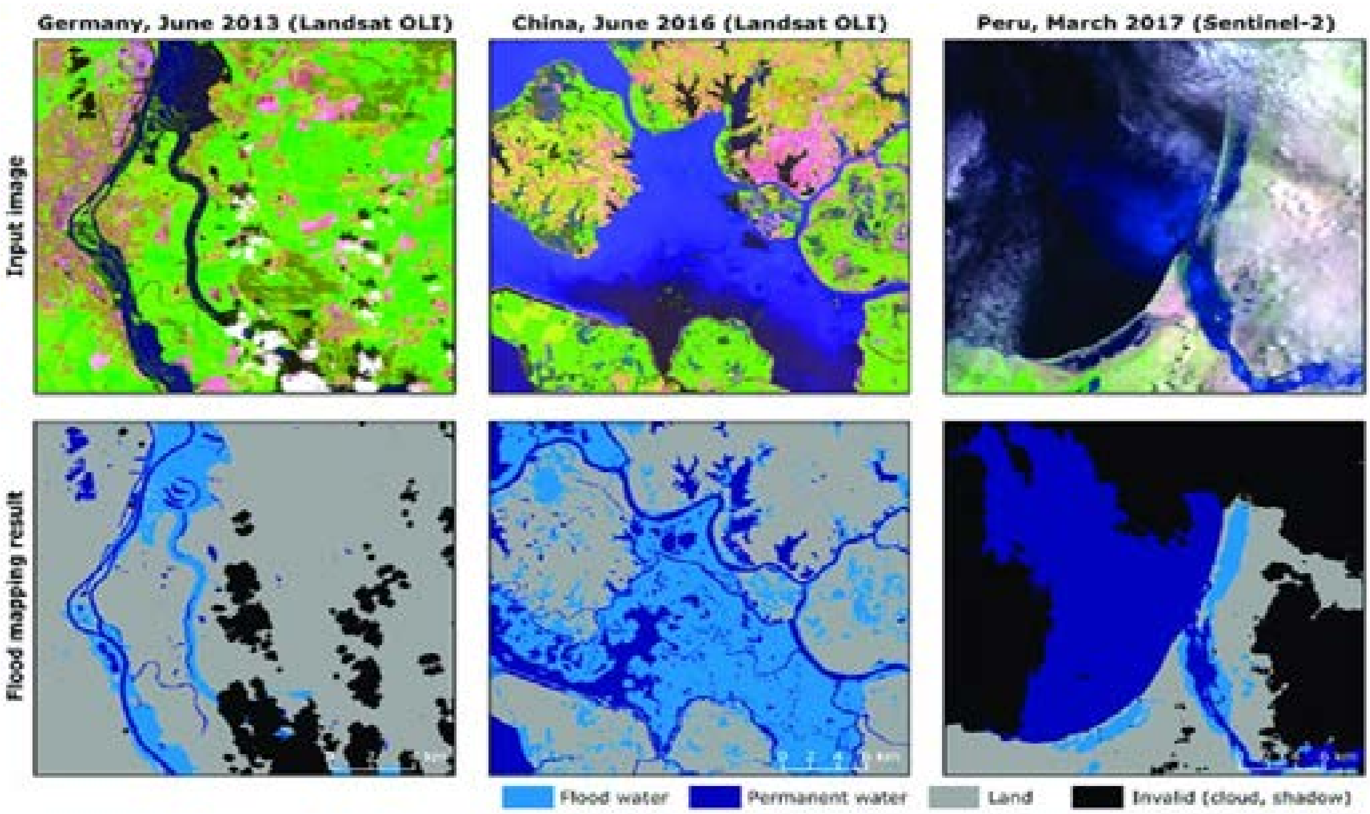


Figure 11. Satellite Image Samples on Flooding

In addition to satellite images, there are two other remote sensing data sources. One of them is known as electromagnetic spectrum data. Electromagnetic energy, produced by the vibration of charged particles, travels in the form of waves through the atmosphere and the vacuum of space. These waves have different wavelengths (the distance from wave crest to wave crest) and frequencies; a shorter wavelength means a higher frequency. Some, like radio, microwave, and infrared waves, have a longer wavelength, while others, such as ultraviolet, x-rays, and gamma rays, have a much shorter wavelength. Visible light sits in the middle of that range of long to shortwave radiation. This small portion of energy is all that the human eye is able to detect. Instrumentation is needed to detect all other forms of electromagnetic energy. NASA instrumentation use the full range of the spectrum to explore and understand processes occurring on Earth and on other planetary bodies (Wieland, & Martinis, 2019).

Electromagnetic spectrum ranges have different spectrum responses to temperature and ground object types, which is also the basis of using satellite remote sensing data for a variety of emergency monitoring and post disaster loss assessment. The monitoring platform can use the data of multiple Sun-synchronous orbit satellites and medium and low-resolution geosynchronous orbit satellites to monitor the disasters in the monitoring area, automatically obtaining the location, quantity, start time and other information about disasters, and dynamically recording and tracking the changes of the situation through the time axis. Figure 12 shows the wavelength spectrum and special signatures of Earth features. These signature data are very useful for finding out some detailed features on

Earth, for example, land coverage, crop, tree, and plant identification and density analysis, as well as vegetation coverage for a targeted area (Gao, 1996).

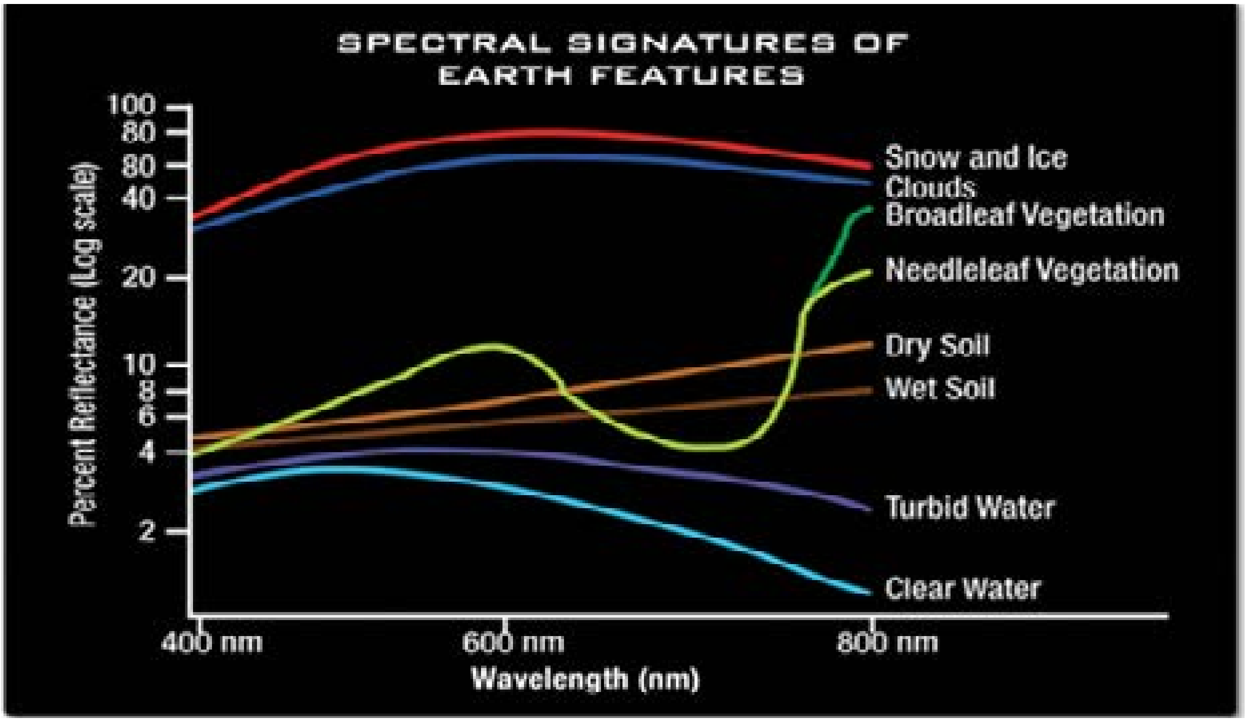


Figure 12. Wavelength Spectrum and Special Signatures of Earth Features

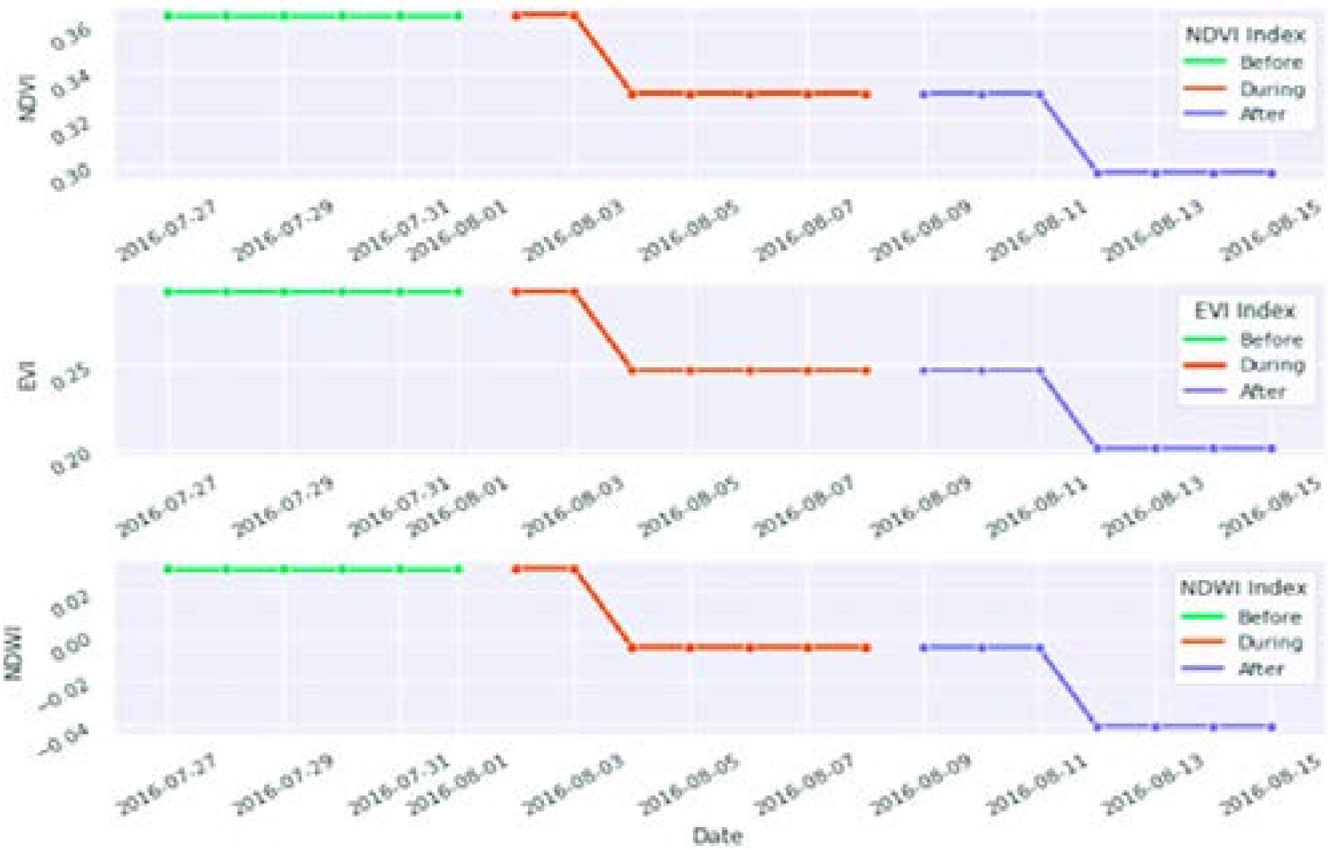


Figure 13. Historical NDVI, EVI, and NDWI Index Data in 2016 during Wildfire in California

Based on wavelength spectrum, scientists have developed a number of remote sensing-derived normalized difference indexes, as described below and shown in Figure 13. Sample data of these indexes are given by Gao and his student group (1996) to compare and analyze the wildfire impacts on land vegetation in California. The Normalized Difference Vegetation Index (NDVI) is a dimensionless index that describes the difference between visible and near-infrared reflectance of vegetation cover and can be used to estimate the density of green on an area of land (Weier & Herring, 2000). It also could be used to analyze the wildfire in a given area (Wieland & Martinis, 2019).

Normalized Difference Water Index (NDWI) may refer to one of at least two remote sensing-derived indexes related to liquid water. One is used to monitor changes in water content of leaves, using near-infrared (NIR) and short-wave infrared (SWIR) wavelengths, proposed by Gao in 1996. Another is used to monitor changes related to water content in water bodies, using green and NIR wavelengths, defined by McFeeters in 2013. The range of application of NDWI (Gao, 1996) spreads from agricultural monitoring for crop irrigation (Gao, 1996) and pasture management (NASA, 2021) to forest monitoring for assessing fire risk and live fuel moisture (Gao, 1996), particularly relevant in the context of climate change. These indexes could also be used to measure the burned area and environment impacts after wildfires.

Emergency Message Analysis AI Solution

Smart Multiple Emergency Message Analysis Processing

Data collected from social networks and mobile applications may include text, pictures, audio and video, some of which report emergencies and some of which belong to responses reported by consumers. Some of the data reported for emergency events are closely related to the response to the emergencies, while others are not closely related to the emergencies. Therefore, an AI-based platform is needed to analyze and judge these data, so as to extract valuable emergency-related information (Gao, David & Dhar, 2019).

The AI emergency message analysis platform we propose to build has the intelligent data processing functions of hierarchical and multi-dimensional, which can separate the text, picture, audio and video data in the emergency message, and use different technologies for identification and analysis. The message analysis module in the platform can judge the correlation between the content contained in each emergency message. For the emergency messages judged as valuable by the platform, the cross check between multiple messages will be carried out, so as to remove the wrong data in the message and improve the efficiency of message handling.

The detailed AI-powered emergency message processing information flow structure is given in Figure 14. It consists of three steps, which are summarized below.

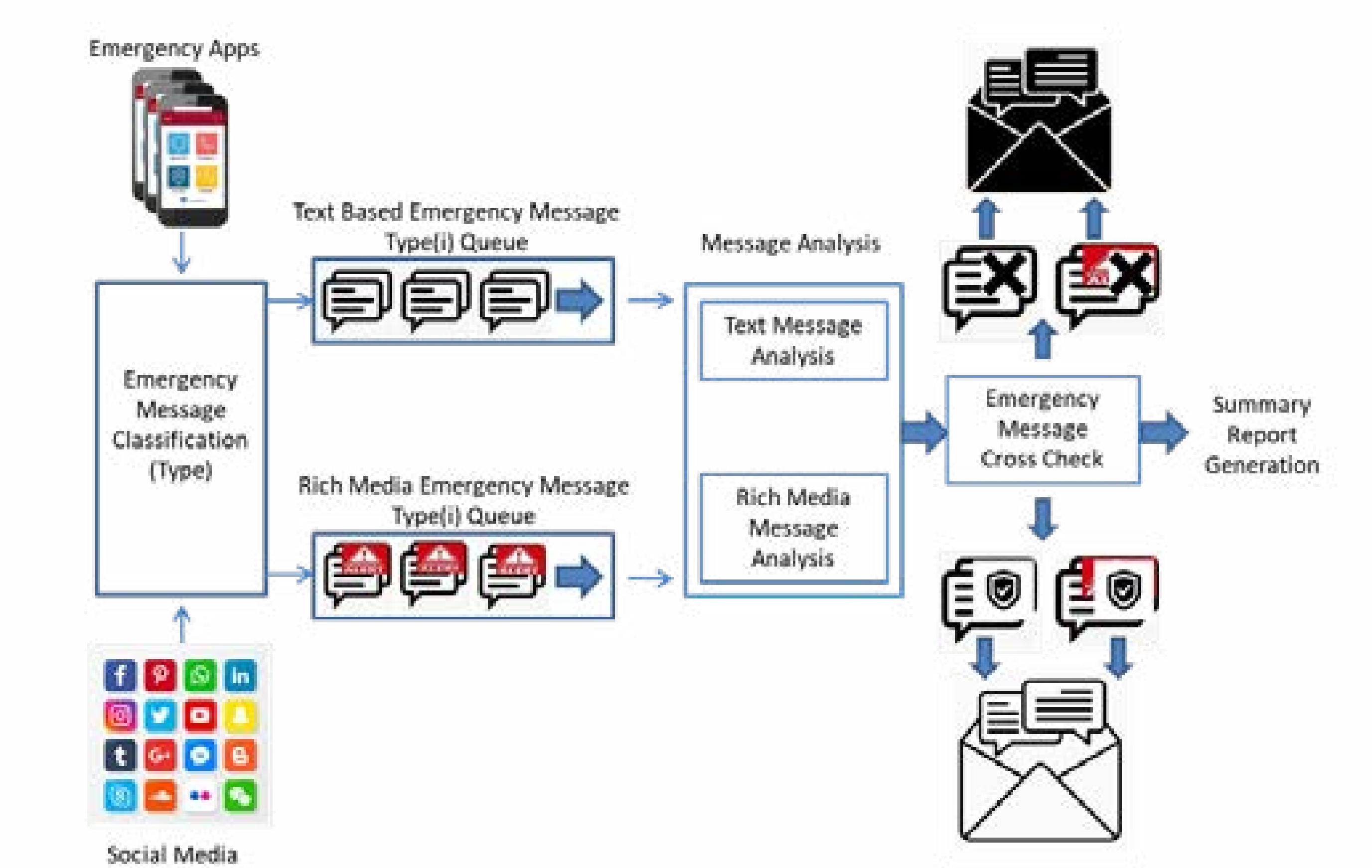


Figure 14. Smart Multiple Emergency Message Analysis

Step #1- Emergency Message Classification – In this step, each received emergency message and its responses are collected, processed, and classified into different groups based on the pre-defined emergency types: a) text-based messages, and b) rich-media messages (that include photos, video and audio). These messages are placed into two different message queues and sent to Emergency Message analysis in Step #2 for further processing. The detailed descriptions about Emergency Message Classification are given in the next section.

Step #2 – Emergency Message Analysis – Emergency Message Analysis in Step #2 includes two parts. One of them is Text Message Analysis, which is used to process text-based emergency messages based on selected artificial intelligence techniques for text analysis. The major objective is to understand and obtain the primary information items from the received emergency alerts and responses, including the types of alerts, and emergency details. The other part is known as Rich Media Message Analysis, which is used to process emergency responses with rich media contents (such as photos, videos, and audios) from the public users on social media and mobile apps. The next section discusses the detailed machine learning models and techniques for building emergency message analysis.

Step #3 - Emergency Message Cross Checker – This step is necessary to cross check real-time collected emergency responses from diverse social media and emergency mobile apps to filter out the invalid, inconsistent, or even untrustworthy messages, based on the results from emergency message analysis, and selected machine learning models, to predict and evaluate the trustworthiness level (or index) for each emergency message. Later, each set of related emergency messages/responses are further validated and analyzed based on their correlations, consistency, and trustworthiness.

Emergency Message Reporting Dashboard - Similar to a virtual map, each event is drawn on the dashboard according to the event name, time, place, person, activity content, scale and other representative elements contained in the emergency message. Emergency messages with similar contents will result in multiple drawings on the same dashboard coordinates. By analyzing the similarity and aggregation degree of each drawing on the dashboard, the content described by each emergency message can be scored. The score can be used in the subsequent analysis module to evaluate the reliability and availability of emergency messages.

Smart Emergency Message Detection and Classification

This module is the first important module to analyze emergency messages in the platform. There are many social media and mobile applications, and the expression and style of messages in each application are different. In addition, many emergency messages contain not only text data, but a large number of pictures, audio and video data. For different types of data, format conversion is required first, and then the converted data is sent to different models for detection and classification. Finally, text alert, rich media alert, text response and rich media response are distinguished. Figure 15 describes the function and working logic of this module.

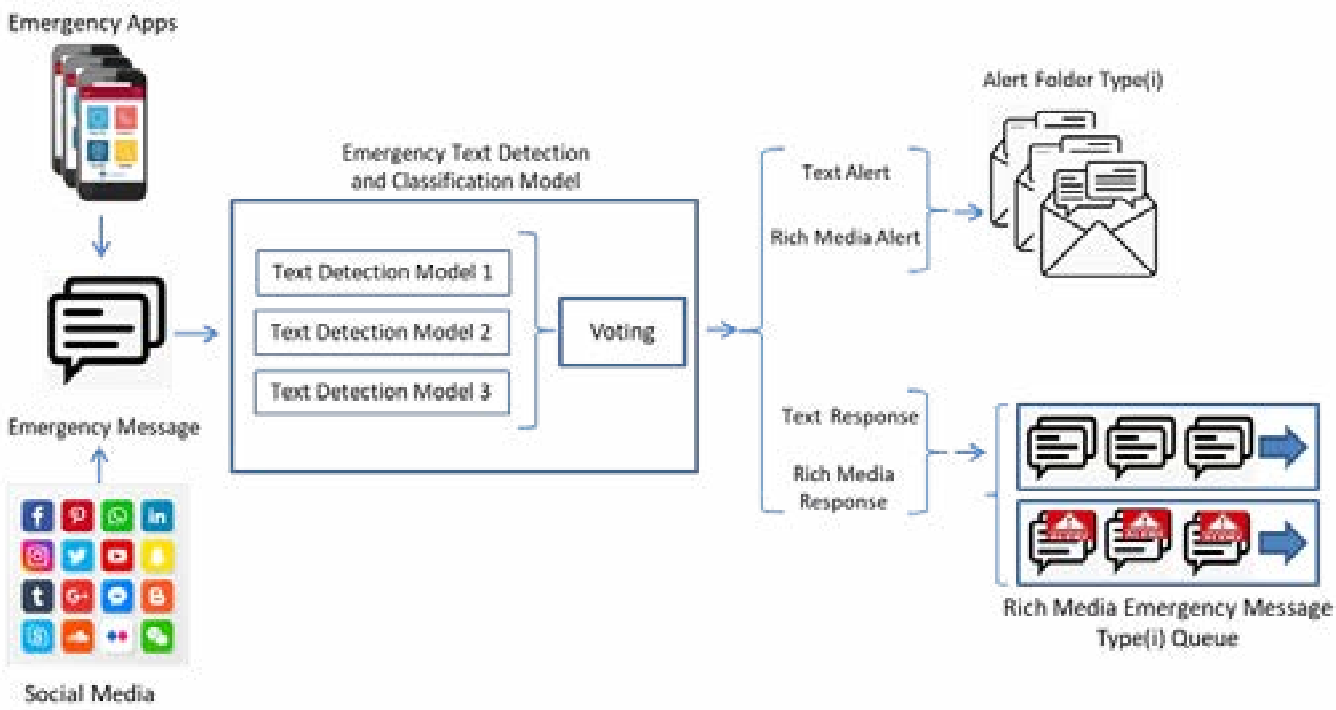


Figure 15. Smart Emergency Message Detection and Classification

Step #1- Multi model emergency detection and classification – In this step, the emergency messages collected from social media and mobile applications are input into multiple different types of models for parallel analysis. Because the working mechanism of various models is different, the detection and classification results of emergency messages are also different. Therefore, the output results of each model will be voted in the next step. The detected and classified emergency messages will be divided into four categories: Text alert, rich media alert, text response and rich media response.

Step #2 - Voting selection of multi model detection classification results – This step is to vote and select the detection and classification results output by multiple models in the previous step so as to select the results with high recognition accuracy and remove the unreliable analysis output results.

Step #3 - Send the detected and classified emergency messages to different queues – The emergency messages output in the previous step have been divided into four categories, which will be analyzed by different AI modules. Therefore, we need to put all kinds of emergency messages into different alert folders and message queues in this step. Specifically, text alert and rich media alert will be put into different alert folders by type. Text response and rich media response will be put into various types of rich media emergency message queue in order.

Emergency Text Message Analysis

After the analysis and classification of emergency messages in the previous stage, the output data is divided into emergency text messages and emergency rich media messages. This module analyzes the content of text type emergency messages so as to obtain emergency alert information and alert response information. Figure 16 describes the functions and working logic of this module.

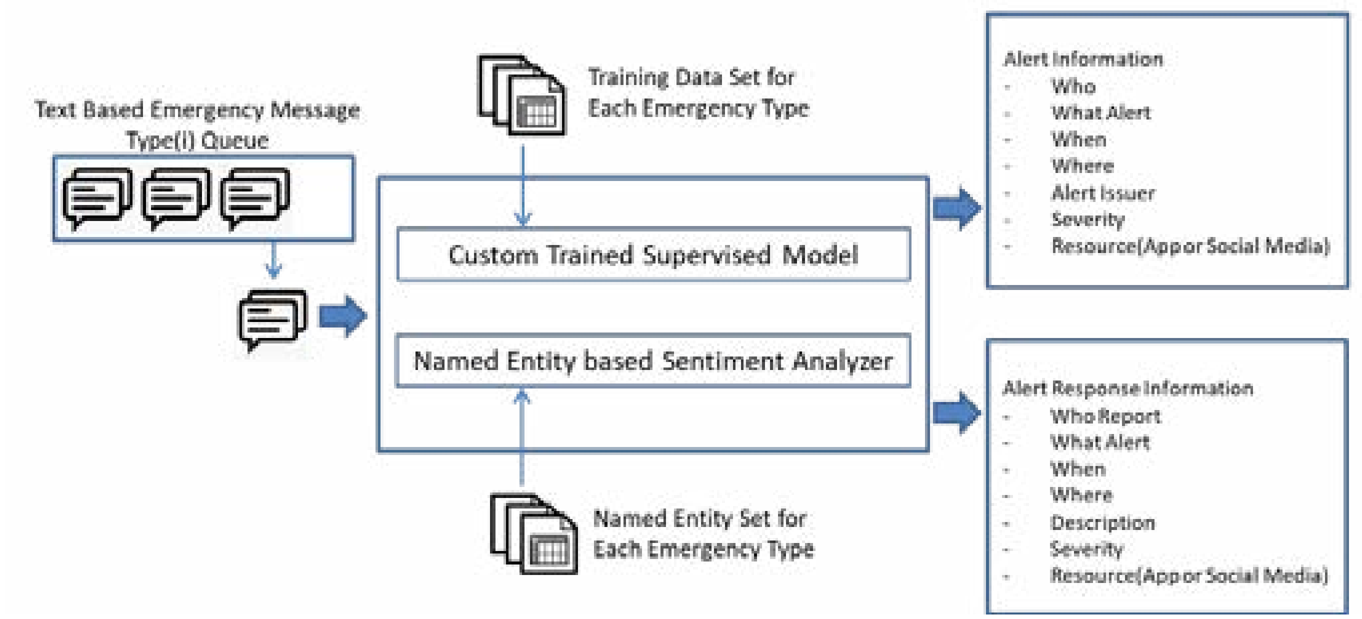


Figure 16. Smart Emergency Text Message Analysis

Step #1- Take out the emergency message from the queue and input the text analysis model – This step is to take data from different types of text-based emergency message queues and send them to custom-trained supervised model and named entity-based sentient analyzer for analysis.

Step #2 – Text-Based Emergency Message Analysis – AI model analyzes the input emergency message according to training data set for each emergency and the named entity set for each emergency type. The output results of the analysis are divided into two categories: alert information and alert response information. Alert information includes: who, what, alert, when, where, alert issuer, severity, resource. Alert response information includes: who report, what alert, when, where, description, severity, resource.

Smart Rich Media Emergency Message Analysis

The last module mainly discusses the analysis of the text type of emergency messages. This module analyzes and classifies rich media emergency messages. The analysis of rich media emergency messages is more complex than that of text type emergency messages, because rich media emergency messages may contain text data, picture data, audio data and video data at the same time. In addition to the direct analysis of text data, image data, audio data and video data need to be converted or content recognized before the analysis of elements related to emergencies. Figure 17 describes the functions and working logic of this module.

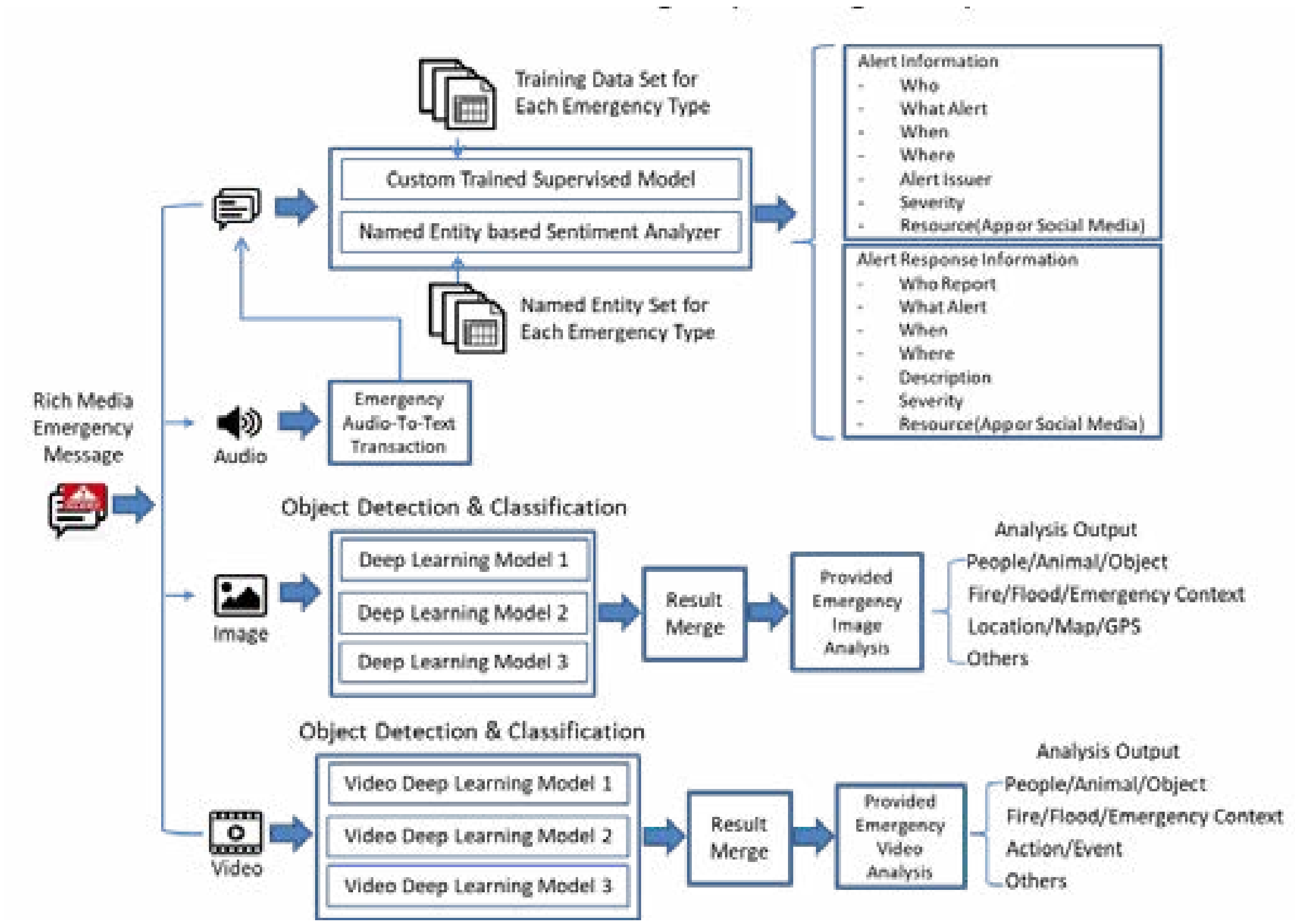


Figure 17. Smart Rich Media Emergency Message Analysis

Step #1- Extract the text data in rich media emergency message for text analysis – Firstly, the text data in rich media emergency message is extracted and directly sent to smart emergency message detection & classification module for text analysis.

Step #2 – Convert the audio data in rich media emergency message into text for text analysis – Perform audio to text conversion on the audio data separated from rich media emergency message, and send the conversion results to smart emergency message detection & classification module for text analysis. Figure 18 shows the general process of converting audio data content recognition into text.

Figure 18. Audio to Text Transaction

There may be many types of emergency message audio data collected. Audio from different sources may be sampled at different rates, or have a different number of channels. If the audio quality is poor, it can be enhanced by applying a de-noising algorithm to eliminate background noise so that the focus is on the audio content analysis in emergency messages. Figure 19 describes the general process of continuous processing of emergency message audio and text conversion through a deep learning model.

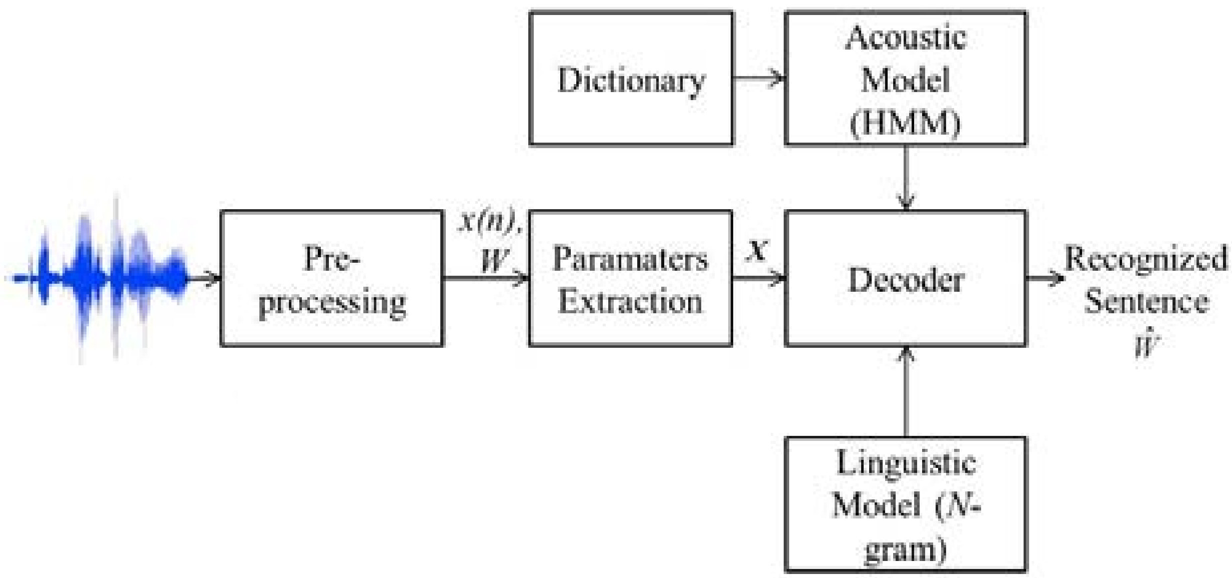


Figure 19. Block diagram of an Automatic Speech to Text [21]

Step #3 - Extract the image data in rich media emergency message for object detection and classification – Input the image data in rich media emergency messages into multiple deep learning models for parallel object detection and classification. Multiple detection and classification results will be merged in subsequent steps. The next topic is the application of various image analysis technologies in video analysis of emergency messages.

The application process of a Convolutional Neural Network (CNN) is relatively uncomplicated. It only needs to train the weight to get the available model. The effect of feature classification is also good, and it is suitable for high-dimensional data processing. The disadvantage is that the initial training of the model needs more data samples. This technology can be used for preliminary target detection and recognition of image data in emergency messages, as shown in Figure 20.

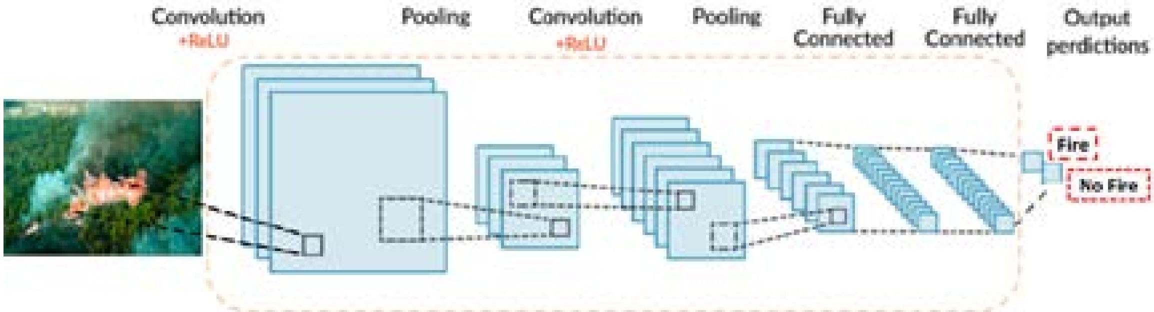


Figure 20. Fire Detection in Image Based on CNN
Source: Tang, Han, & Jiang, 2022.

The neural network Alexnet is widely used. It can flexibly define the number of convolution cores and the number of convolution core layers in front of each block pool layer (Brito, Pereira, Lima, Castro, & Valente, 2020). Optimal sensors can be positioned to detect wildfire. This allows the technology to be defined and applied to a variety of specific scenarios as needed. This technology can be used to detect and recognize complex targets in the image data of emergency messages. For example, it can recognize multiple disaster features in the image at the same time. Figure 21 describes the principle of Alexnet detecting various emergencies.

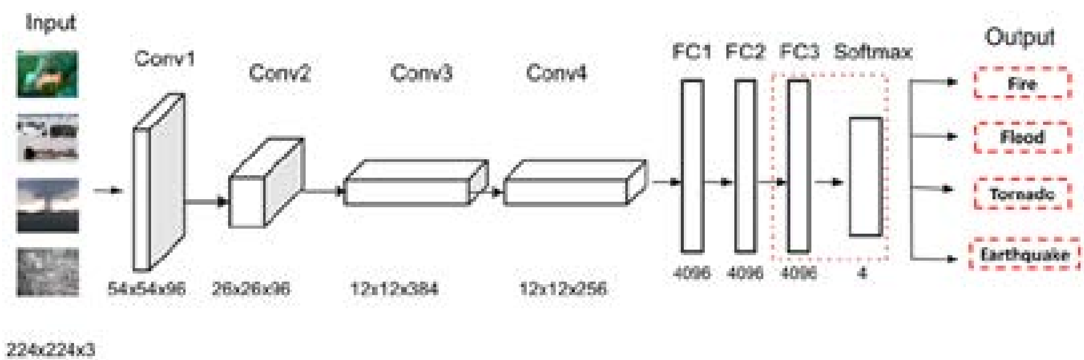


Figure 21. Detection of Emergencies in Image Based on AlexNet

Vgg16, a type of CNN, is also widely used in the field of target detection. The structure of vgg16 is relatively simple, and the time required for model training is relatively short, so it can be quickly deployed to application scenarios (Chen, Yang, Yu, Yue, & Xie, 2018). The disadvantage of vgg16 is that it consumes a lot of performance of computer hardware. This technology can be used in the analysis of specific messages. Figure 22 describes the principle of vgg16 detecting various emergencies.

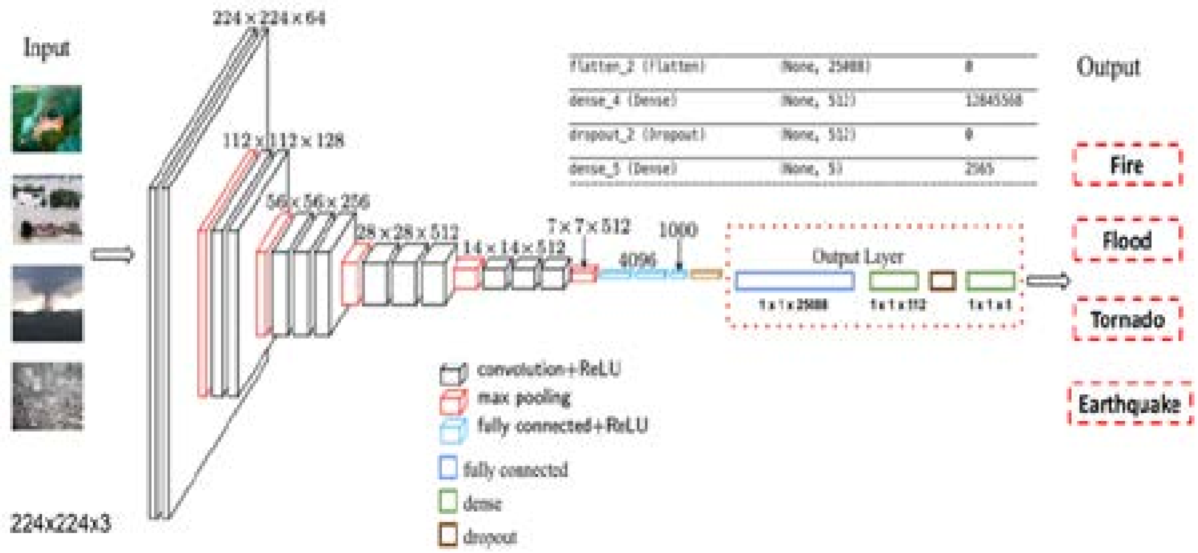


Figure 22. Detection of Emergencies in Image Based on VGG16
Source: Chen, Yang, Yu, Yue, & Xie, 2018

You Only Look Once (YOLO) "allows all objects to be detected in a single algorithm run" (Morgunov, 2023). Yolo has experienced the development process from YOLO 1 to YOLO 5, which significantly improved the performance of object detection. Because the platform needs to analyze a lot of emergency message video data, it is more appropriate to choose this model with high detection performance. Figure 23 describes the principle of YOLO 5 detecting various emergencies.

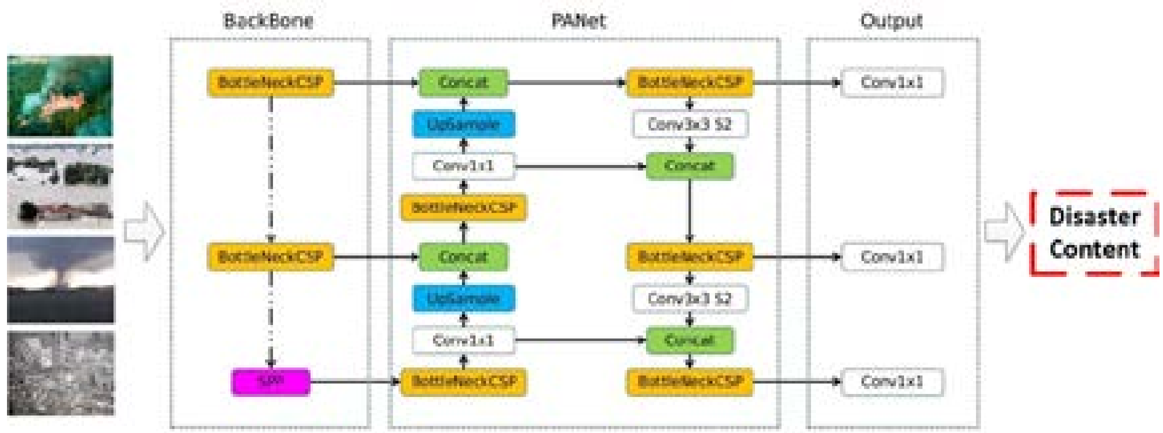


Figure 23. Detection of Emergencies in Image Based on Yolo 5
Source: Overview of model structure about YOLOv5, 2020.

Step #4 - Merge the image data detection and classification results in the rich media emergency message output by multiple deep learning models – Merge the object detection and classification results of rich media emergency messages image output by multiple deep learning models. As shown in the figure below, this function module gives weights to the image detection results output by multiple parallel deep learning models. After the detection results combined with the weight, the analysis results with higher reliability will be transmitted to the subsequent analysis module. Figure 24 describes the merge function principle of rich media emergency message image data detection and classification results.

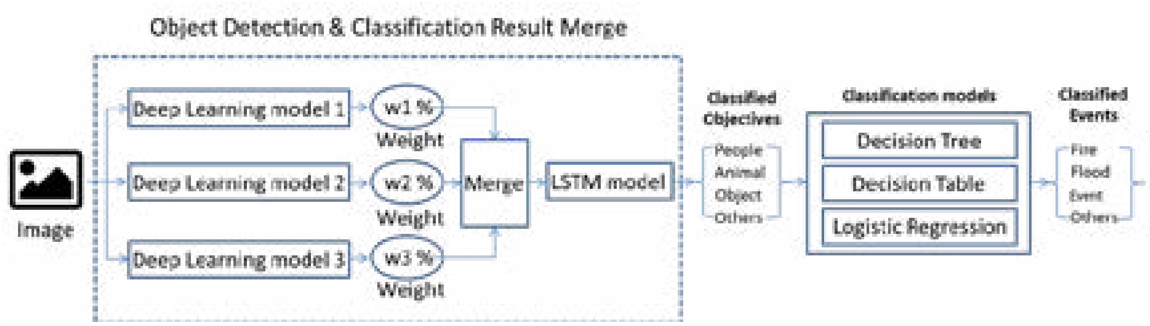


Figure 24. Figure 24: Image Data Detection and Classification Result Merge

Step #5 – Provided emergency message image analysis – The task of this step is to further classify the analysis results of the emergency message image data that have been merged so as to distinguish the analysis result data in line with the characteristics of the emergency. The classification methods that can be selected in this step include decision tree, decision table, logistic regression, softmax regression, random forest, and others. Figure 25 shows the principle of analysis-result classification by taking the decision tree as an example. The output of this stage includes people / animal / object / fire / flood / emergency context / location / map / GPS and others.

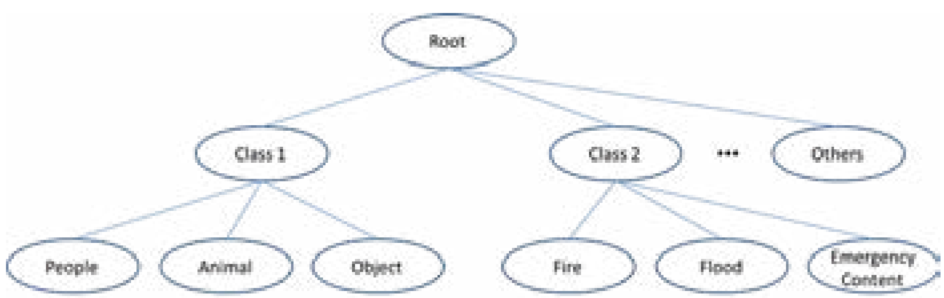


Figure 25. Provided Emergency Message Image Analysis

Step #6 - Extract the video data in rich media emergency message for object detection and classification– Input the video data in the rich media emergency message into multiple deep learning models for parallel object detection and classification. Multiple detection and classification results will be merged in subsequent steps. The basic analysis method for the video data in the emergency message is to divide the video into multiple independent frames, and each frame can be input as an image into the image data analysis module mentioned above for detection and classification. Video frames can also be combined into short video segments to realize scene analysis. Figure 26 describes the principle of this analysis method.

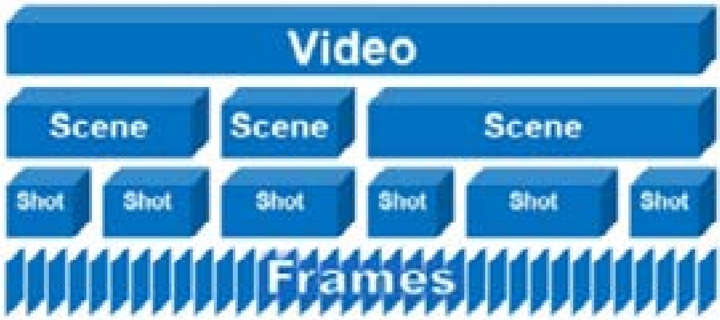


Figure 26. Video Data Segmentation Analysis Method

In addition to the image analysis of video segmentation into independent frames, researchers can also analyze the continuous information in the video in more dimensions, so as to find more anomalies (Sultani, Chen, & Shah, 2018). This technology is an effective supplement to the image analysis method. Figure 27 describes the working principle of this technical scheme.

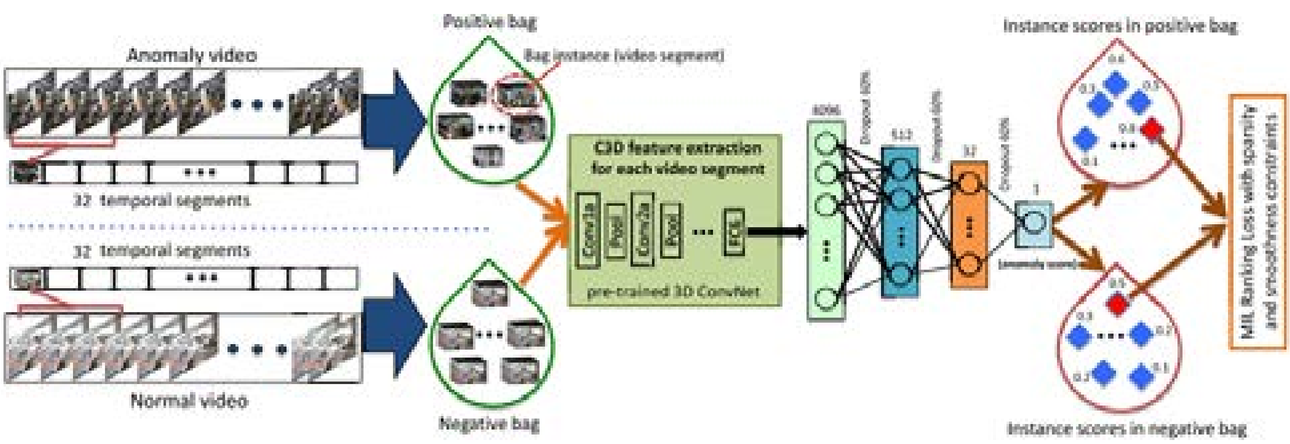


Figure 27. Anomaly Detection Method of Rich Media Emergency Message Video Data

Source: Real-world anomaly detection in surveillance videos. (n.d.).

Step #7- Merge the video data detection and classification results in the rich media emergency message output by multiple deep learning models – Merge the object detection and classification results of rich media emergency messages video output by multiple deep learning models. As shown in the figure below, this function module gives weights to the video detection results output by multiple parallel deep learning models. After the video detection results are combined with the weight, the analysis results in higher reliability, which will be transmitted to the subsequent analysis module. Figure 28 describes the merge function principle of rich media emergency message video data detection and classification results.

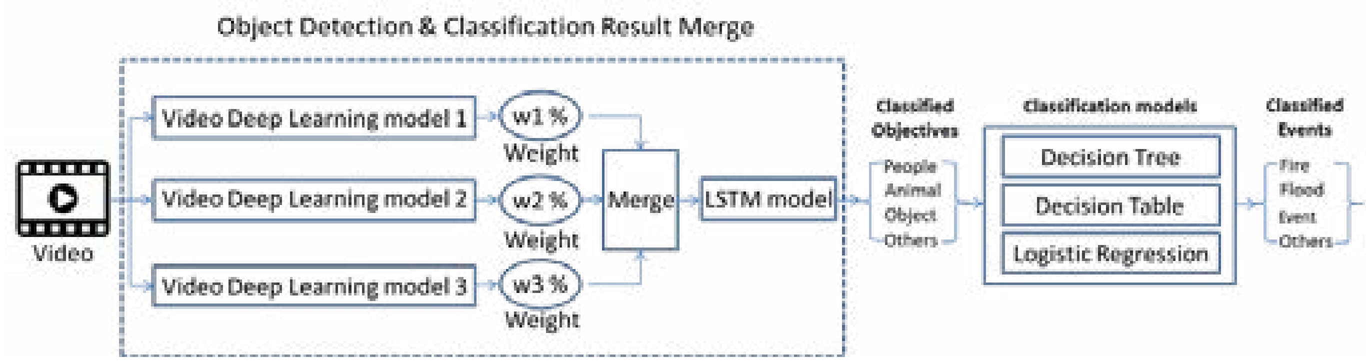


Figure 28. Object Detection & Classification Result Merge

Step #8 – Provided emergency message video analysis – The task of this step is to further classify the analysis results of the emergency message video data that have been merged, so as to distinguish the analysis result data in line with the characteristics of the emergency. The classification methods that can be selected in this step include: decision tree, decision table, logistic regression, softmax regression, random forest, and others. Figure 29 shows the principle of analysis result classification by taking the decision tree as an example. The output of this stage includes: people / animal / object / fire / flood / emergency context / action / event, and others.

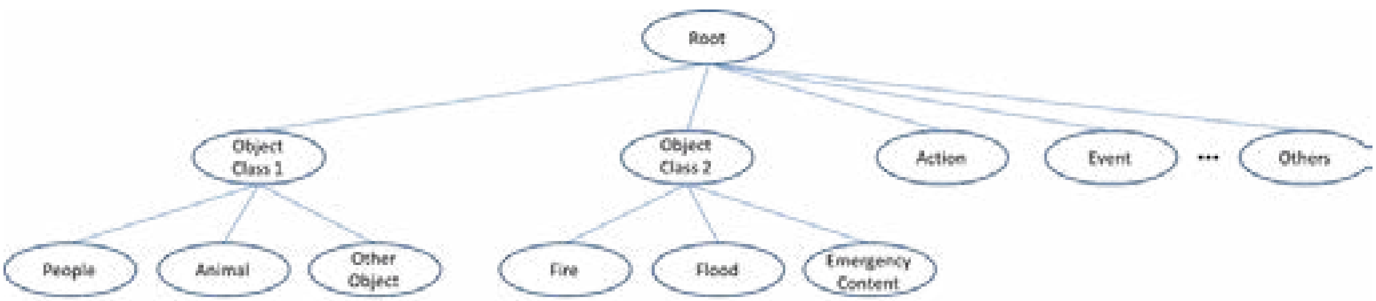


Figure 29. Provided Emergency Message Video Analysis

Text-Based Emergency Message Cross Check

The main function of this module is to analyze and judge the relevance and consistency between multiple text type emergency messages. By comparing the consistency of the description of key factors such as time, place and content of emergencies in multiple messages, the reliability of events described in messages is verified and scored. The input data of this analysis step is classified emergency text messages output by a smart text message analysis module. The output data of this module is the emergency message data set that has been cross verified and scored and summary reported. Figure 30 describes the principle of cross checking for text-based emergency messages.

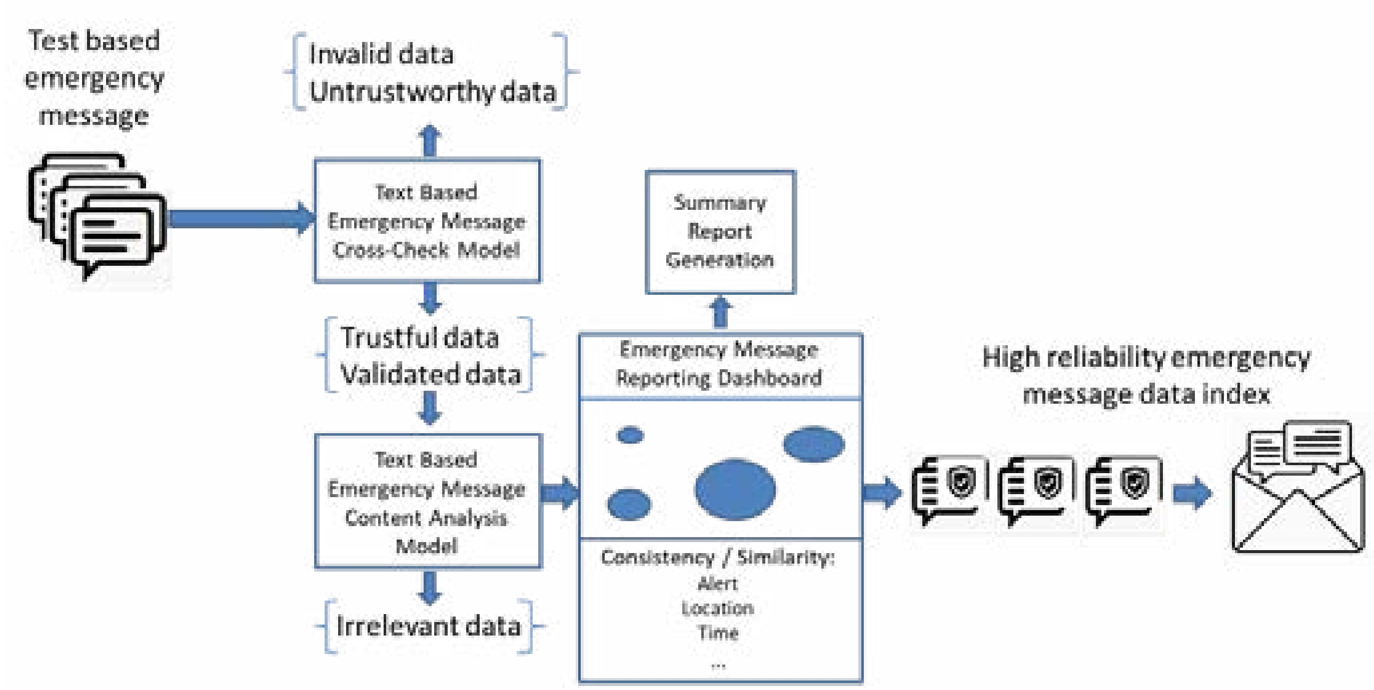


Figure 30. Text-Based Emergency Message Cross Check

Step #1 - Send text-based emergency message to cross check model for availability analysis

This step analyzes the availability of the content contained in each text-based emergency message itself. The focus of the analysis includes but is not limited to: the integrity of the content description, the correlation between the content and emergencies, the logical rationality of the content itself, and so on.

Step #2 - Extract the key elements describing emergencies in text-based emergency messages

The text-based emergency messages checked in the previous step contain relatively complete emergency descriptions. In this step, the elements of the description of emergencies in each message will be extracted so as to quantify several main attributes of the described emergencies, such as event topic, time, place, activity and so on.

Step #3 - Analyze the consistency and similarities between the contents described by multiple emergency messages based on emergency message reporting dashboard technology

Draw the contents described by multiple emergency messages output in the previous step on the emergency message reporting dashboard according to time, place, activity and other elements. The similarity and consistency between each event description and other events are analyzed to score it. Multiple emergency messages with high content description consistency will get relatively higher scores.

Step #4 - Generate credible emergency message index data set

Save the rated emergency messages in turn and generate an index for use by other functional modules in the platform, and generate a summary report at the same time.

Rich Media Emergency Message Cross Check

The main function of this module is to analyze and judge the correlation and consistency between multiple rich media type emergency messages. By comparing the consistency of the description of key factors, such as time, place and content of emergencies in multiple messages, the reliability of events described in messages is verified and scored. The input data of this analysis step is the classified rich media emergency messages output by smart rich media message analysis module. The output data of this module is the cross verified and scored emergency message data set and summary report. Figure 31 describes the principle of cross checking for rich media emergency messages.

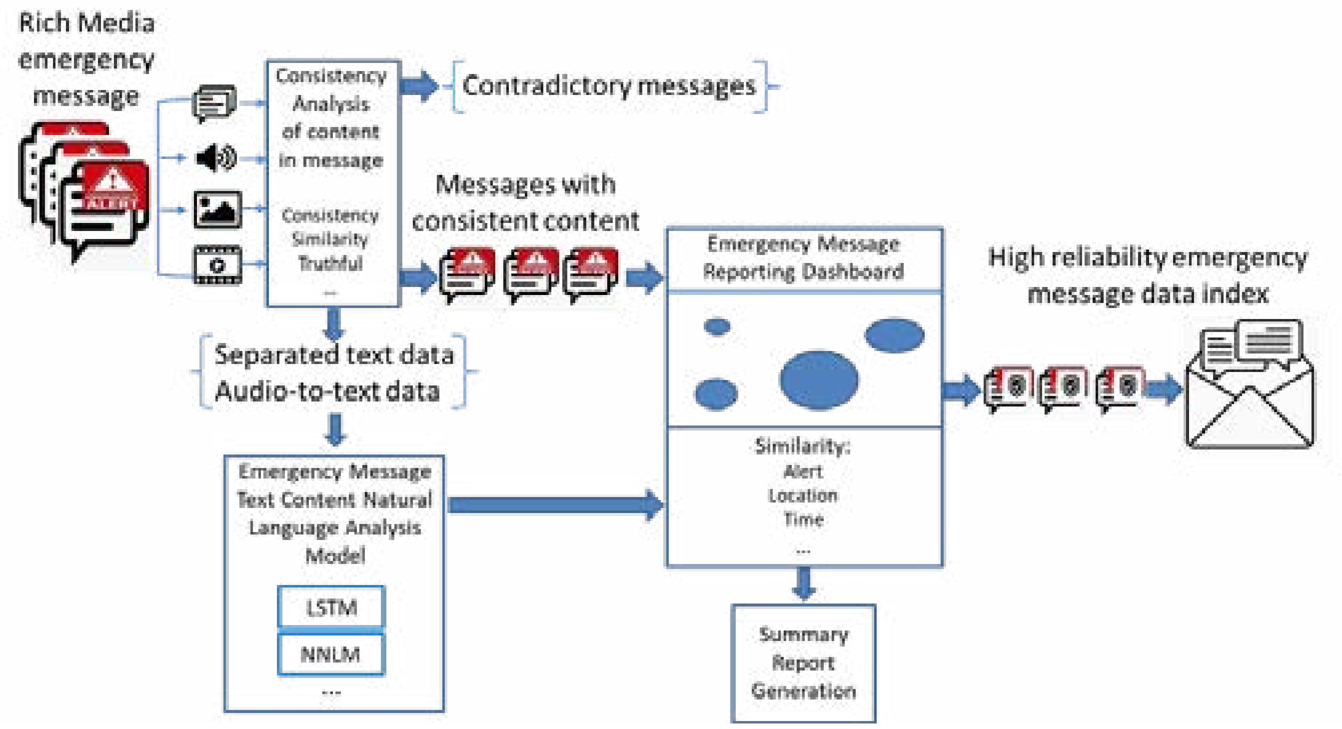


Figure 31. Rich Media Emergency Message Cross Check

Step #1 - Send text-based emergency message to cross check model for availability analysis

Because rich media emergencies contain a lot of information, in this step, first verify the consistency of the content contained in each rich media emergency message. Analyze whether there is obvious self-contradictory logic between the text description content in the message, the content described in the audio data, and the object and scene contained in the image and video, so as to remove useless messages with chaotic content.

Step #2 - Extract the key elements describing emergencies in text-based emergency messages

Send the emergency messages with consistent content verified in the previous step to the emergency message reporting dashboard. Draw the emergency content described by multiple emergency messages on the emergency message report dashboard according to time, place, activity and other elements. Analyze the similarity and consistency between each event description and other events, and then score them. The scores of multiple emergency messages with high content description consistency are relatively high.

Step #3 - Analyze the consistency and similarity between the contents described by multiple emergency messages based on emergency message reporting dashboard technology

The text data contained in rich media emergency message and the text data converted from audio data will be sent to the natural language analysis model. This step of analysis will extract more abundant description information about the content of emergencies from the text data. Then, it will send this description information to the emergency message reporting dashboard to participate in the drawing of the event characteristic diagram, together with other messages.

Step #4 - Generate credible emergency message index data set

Save the rated emergency messages in turn and generate an index for use by other functional modules in the platform, and generate a summary report at the same time.

Conclusion

Challenges include developing the consumer cell phone app to deliver the accurate data about an event, and ensuring delivery capability through improved IPAWS and WEA delivery system infrastructure. When cell towers burn down or lose power, delivery of messages fails. The cell phone app does not resolve the problem of the loss of cell towers. Options for buying emergency connectivity also exist, but would require a pre-emergency action by the cell phone owner. Technologies exist to collect, filter, analyze and create reliable credible emergency message data sets that could be broadcast to community consumers and first responders in near real time.

Glossary

AI – artificial intelligence: leverages computers and machines to mimic the problem solving and decision-making capabilities of the human mind. They can iteratively improve themselves based on the information that they collect.

API – Application Programming Interface: application refers to any software with a distinct function. Interface can be thought of as a contract of service between two applications. This contract defines how the two communicate with each other using requests and responses.

APP – application: a software program that runs on a computer, such as a smart phone.

BERT – Bidirectional Encoder Representations from Transformers: an open-source machine learning framework for natural language processing, that is designed to help computers understand the meaning of ambiguous language and text.

Big Data – data that contains greater variety, arriving in increasing volumes and with more velocity; larger more complex data sets, especially from new data sources. Traditional data processing software cannot manage the volume of data.

Drone – any remotely guided or autonomous vehicle.

IOT – internet of things: physical objects with sensors, processing ability, software and other technologies that connect and exchange data with other devices and systems over the internet or other communications networks.

Milling – a term coined by Dennis Mileti (2019) to describe the process people use to compare possible alterative actions during a disaster before choosing a response action.

MTL – multi-task learning approach.

NER – Named Entity Recognition: A system used to locate and classify names entities mentioned in unstructured text into pre-defined categories, such as person, name, organization, locations and others.

OODA – observation, orientation, decision and action; a term coined by John Boyd to explain how decisions are made in high pressure situations for military operations, also applied to cyber security and competitive markets.

Rich media messages – digital term for a message that includes advanced features like video, audio and others elements that encourage the recipient to interact and engage with the content.

Sense making – a term coined by Lugtu (2019) to define “how we structure the unknown so as to be able to act on it.”

Smart Cities – uses digital technology to connect, protect and enhance the lives of citizens. IOT, cameras and other sensors act as a nervous system, providing the city operator and citizens with constant feedback so they can make informed decisions.

Smart phone – a portable computer device that combines mobile telephone and computing functions into one unit.

UAV – unmanned aerial vehicle: any flying aircraft piloted by software or remote control, and which is capable of reuse.

VGG-16 – a computer innovation, convolutional neural network model for image classification and object detection at a large scale.

YOLO – a computer neural network that makes predictions of bounding boxes and class probabilities all at once for object recognition.

References

Amin, R. (2020). Introduction of 5G as a next-generation mobile network. ABC Research Alert, 8(3), 129-138. https://doi.org/10.18034/abcra.v8i3.496

Bean, H., Sutton, J., Liu, B.F., Madden, S., Wood, M.M. & Mileti , D.S. (2015) The Study of Mobile Public Warning Messages: A Research Review and Agenda, Review of Communication, 15:1, 60-80. DOI: 10.1080/15358593.2015.1014402

Bhandari, P. (2022). Inductive Reasoning. Scribbr. https://www.scribbr.com/methodology/inductive-reasoning/

Bicans, J., Kviesis, K., & Avotins, A. (2019). IoT camera-based approach to capture and process SI-NDVI sensor data for industrial tomato greenhouse. 2019 IEEE 7th IEEE Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE). https://doi.org/10.1109/aieee48629.2019.8977127

Brito, T., Pereira, A., Lima, J., Castro, J., & Valente, A. (2020). Optimal sensors positioning to detect forest fire ignitions. Proceedings of the 9th International Conference on Operations Research and Enterprise Systems. https://doi.org/10.5220/0009386404110418 24.

Canton, L. (2006). Emergency management: A Historical Perspective. https://doi.org/10.1002/9780470119761.ch1Chen, X., Yang, H., Yu, J., Yue, W., & Xie, Y. (2018). A feature extraction strategy of fire hole video based on VGG16 and migration learning. 2018 Chinese Automation Congress (CAC). https://doi.org/10.1109/cac.2018.8623274

Coram, R. (2002). Boyd: The Fighter Pilot Who Changed the Art of War. New York, NY: Back Bay Books/Little, Brown & Co.

Edmonds, M. (n.d.). Top 5 car gadgets. How Stuff Works. https://electronics.howstuffworks.com/gadgets/automotive/5-car-gadgets.htm

Edwards, F.L., Liu, K., Hughes, A.L., Gao, J., Goodrich, D.C., Barner, A. and Herrera, R. (2022). Best Practices in Disaster Public Communications: State of the Practice in Communicating Information, Building Trust and Compelling Action, using Traditional and Social Media, and Developing a Cell Phone App. Mineta Transportation Institute. In press.

Ennis, R.H. (2010). A super-streamlined conception of critical thinking. http://criticalthinking.net/

FEMA. (n.d.) FEMA Mobile Products. https://www.fema.gov/about/news-multimedia/mobile-products

Gao, B.A. (1996). NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sensing of Environment. 58 (3): 257–266. doi:10.1016/S0034-4257(96)00067-3

Gao, J. , David C. & Subhankar Dhar, (2019). Mass Warning Study. Unpublished report to the

City of San José, California.

Hall, C., & Ward, K. (2021). Enabling access and use of NASA earth science data in disaster situations with thematic data pathfinders. Geological Society of America Abstracts with Programs, vol. 53, #6. https://doi.org/10.1130/abs/2021am-367665

Hammond, G. (2001). The Mind of War: John Boyd and American Security. Washington, DC: Smithsonian Institution.

Hansen, L. (2015). 8 drivers who blindly followed their GPS into disaster. The Week. https://theweek.com/articles/464674/8-drivers-who-blindly-followed-gps-into-disaster

Hartman, F. & Ashrafi, R. (2004). Development of the SMARTTM project planning framework. International Journal of Project Management, 22(6), 499-510. https://doi.org/10.1016/j.ijproman.2003.12.003

Huang, H., & Guo, S. (2020). Smart phone-based emergency communication. In Akerkar, R., Big Data in Emergency Management: Exploitation Techniques for Social and Mobile Data, 131-147. https://doi.org/10.1007/978-3-030-48099-8_7

Iowa Department of Public Safety. (n.d.). Intelligence production cycle. Division of Intelligence and Fusion Center. https://dps.iowa.gov/divisions/intelligence/intel-cycle#:~:text=Analysis%20and%20production%20is%20the,contradictory%20%2D%20and%20preparing%20intelligence%20products.

Kaplan Lawyers, PC. (n.d.). GPS Navigation Accidents in New York City. https://www.kaplanlawyers.com/vehicle-accident-attorneys/car-accidents-gps/

Kwan, C. (2021). Safety enhancement of UAVs from the signal processing's perspectives: A bird's eye view. Drones, 5(1), 16. https://doi.org/10.3390/drones5010016

Lewis, S. (2019). OODA Loop. TechTarget. June. https://www.techtarget.com/searchcio/definition/OODA-loop

Lugtu, R.C. (2019). Sense making – an emerging leadership skill. Business World. April 12. https://www.bworldonline.com/sense-making-an-emerging-leadership-skill/

McFeeters, S.K. (2013). Using the Normalized Difference Water Index (NDWI) within a Geographic Information System to Detect Swimming Pools for Mosquito Abatement: A Practical Approach. Remote Sens. 2013, 5, 3544-3561. https://doi.org/10.3390/rs5073544.

Menon, K. P. & Kala, L. (2017). Video surveillance system for realtime flood detection and mobile app for flood alert. 2017 International Conference on Computing Methodologies and Communication (ICCMC). https://doi.org/10.1109/iccmc.2017.8282518

Mileti, D.S. (2019). Modernizing Public Warning Messaging. Presentation at the National Tsunami

Hazard Mitigation Program (NTHMP) Annual Meeting, San Diego, CA, January 30. https://nws.weather.gov/nthmp/2019annualmeeting/Mileti.pdf

Morgunov, A. (2023, January 24). Object Detection with YOLO: Hands-on Tutorial. Accessed 2/23/23 from https://neptune.ai/blog/object-detection-with-yolo-hands-on-tutorial

NASA. (2021). What is remote sensing? Earthdata, February 21. https://earthdata.nasa.gov/learn/backgrounders/remote-sensing

NOAA-USGS Debris Flow Task Force. (2005). NOAA-USGS debris-flow warning system—Final report. Circular 1283. https://doi.org/10.3133/cir1283

Overview of model structure about YOLOv5. (2020). Ultralytics, Issue #291. https://github.com/ultralytics/yolov5/issues/280

Peha, J. M. & Yu, M. S. (2017). Broadcasting emergency information to non-English speakers. 2017 IEEE International Symposium on Technologies for Homeland Security (HST). https://doi.org/10.1109/ths.2017.7943497

Pew Research Center. (2020). Americans' Views of Government: Low Trust, but Some Positive Performance Ratings. September. Retrieved from file:///C:/Users/002060436/Documents/Downloads/PP_09.14.20_views.of_.government.full_.report%20(2).pdf

Rudisill, K. (2011). Social movement media in the emergency (India). (2011). In Downing, J.D.H. (editor). Encyclopedia of Social Movement Media. https://doi.org/10.4135/9781412979313.n219

Sultani, W., Chen, C. & Shah, M. (2018). Real-World Anomaly Detection in Surveillance Videos. Semantic Scholar. DOI:10.1109/CVPR.2018.00678

Tang, Z., Han, Y., & Jiang, S. (2022). Research on CNN fire detection based on parallel decision-layer. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4049416

Trepekli, K., Westergaard-Nielsen, A., & Friborg, T. (2020). Application of drone borne LiDAR technology for monitoring agricultural biomass and plant growth. EGU General Assembly. https://doi.org/10.5194/egusphere-egu2020-9802

Trimarchi, M. (n.d.). Do car GPS devices cause accidents? How Stuff Works. https://electronics.howstuffworks.com/gadgets/automotive/car-gps-accidents.htm

Wei, Q., Xia, Y., & Jiang, S. (2013). A novel prewhitening subspace method for enhancing speech corrupted by colored noise. 2013 6th International Congress on Image and Signal Processing (CISP). https://doi.org/10.1109/cisp.2013.6743870

Weier, J. & Herring, D. (2000) . Uncertainty Analysis of Spatial Autocorrelation of Land-Use and

Land-Cover Data within Pipestem Creek in North Dakota. Journal of Geoscience and Environment Protection, Vol.5 No.8, August 2, 2017.

Wieland, M., & Martinis, S. (2019). A modular processing chain for automated flood monitoring from multi-spectral satellite data. Remote Sensing, 11(19), 2330. https://doi.org/10.3390/rs11192330

Wood, M.M., Mileti, .S., Kano,M., Kelley,M.M., Regan, R. & Bourque, L.B. (2012). Communicating Actionable Risk for Terrorism and Other Hazards. Risk Analysis, Vol. 32, No.4. DOI: 10.1111/j.1539-6924.2011.01645.x

Acknowledgments

This study was funded by the Knight Foundation, which brought the basic research question to the San Jose State University Research Foundation. We are very grateful to Chris Thompson of the Knight Foundation for his continuous interest in and guidance of the research.

The authors are grateful to the many public officials who shared their knowledge and experiences of managing wildfire events and the related public messaging. They are Lee Wilcox, Assistant City Manager, San Jose; Ray Riordan, Director of Emergency Management, San Jose; Erica Ray, Public Information Officer, San Jose Fire Department; Dana Reed, Director of Emergency Services, County of Santa Clara; Chief Stacee Brownlee, Chief of the Ben Lomond Fire Department; Professor Amanda Stasiewicz, Wildfire Interdisciplinary Research Center, San Jose State University; Sergeant Galen Yufszai-Boggs, California National Guard; and several others who preferred to participate anonymously.

They are especially grateful to Dr. Karen E. Philbrick, Executive Director of the Mineta Transportation Institute, for her continuing support of their research and technology transfer; Dr. Hilary Nixon, Deputy Executive Director of MTI, for her assistance with the development of this publication and the webinar; Alverina Weinardy, MTI Public Programs Coordinator, and Minhvy Tran, Graphic Design Student Assistant, for their assistance with the creation of this publication; and Lisa Rose for her editorial services.

Cover image source: Sgt. Galen Yusufzai-Boggs, CNG.

About the Principal Investigator

Frannie Edwards, MUP, PhD, CEM, is professor emeritus at San José State University, and Deputy Director of the National Transportation Security Center at the Mineta Transportation Institute (MTI). She is a Certified Emergency Manager with over 20 years professional experience in California.

To Learn More

For more details about the study, download the full report at transweb.sjsu.edu/research/2254.

MTI is a University Transportation Center sponsored by the U.S. Department of Transportation's Office of the Assistant Secretary for Research and Technology and by Caltrans. The Institute is located within San José State University's Lucas Graduate School of Business.