

Alarming of Multimodel Urban Emergency Events in Crowdsourcing to Social Media using Artificial neural network

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Abstract—An urban emergency event is a sudden, urgent, usually unexpected incident or occurrence that requires an immediate reaction or assistance for emergency situations faced by social group or the recipients of public assistance. For example, the urban resident may face fires, storms, traffic jams and so on. The objective is to Alarming of urban emergency event in crowdsourcing to social media. Social media are computer-mediated technologies that facilitate the creation and sharing of information, ideas, career interests and networks. It would be of great value given the fact that at least 50% some countries are unaware of their condition and will remain unaware until complications appear. In order to describe the real time urban emergency event, the 5W (What, Where, When, Who, and Why) model is proposed. The description of detected events are posted to social media. The proposed system is to fuse Artificial Neural Network (ANN) for filtering irrelevant information, alarming of event efficiently and for better accuracy with multimodel descriptions. The consequence of this system to develop alarming of Multimodel (e.g., text, image, videos) urban emergency events in crowdsourcing to social media.

Index term—Big data, Crowddata, Artificial neural network, Social media

I. INTRODUCTION

Detection about urban emergency events, e.g., fires, storms, traffic jams is of great importance to protect the security of humans. The objective is to detect the urban emergency event in crowdsourcing. Crowdsourcing is a process of acquisition, integration, and analysis of big and heterogeneous data generated by a diversity of sources in urban spaces, such as devices, vehicles, buildings, and

human (Zheng et. al 2016). It would be of great value given the fact that at least 50% some countries are unaware of their condition and will remain unaware until complications appear. With the help of internet of things and Big Data crowdsourcing connects unobtrusive and ubiquitous sensing technologies, advanced data management and analytics models, and novel visualization methods, to create solutions that improve urban environment, human life quality, and city operation systems. The data generated by the IoT camera are stored in the big data because the non-traditional strategies and technologies needed to gather, organize, process, and gather insights from large datasets. Big data is a term for handling large datasets that cannot reasonably be handled by traditional computers or tools due to their volume, velocity, and variety. One of the best-known methods for turning raw data into useful information is by what is known as MapReduce. MapReduce is a method for taking a large data set and performing computations on it across multiple computers, in parallel (LiquiGu et al 2017). Big Data has become important as many organizations both public and private have been collecting massive amounts of domain-specific information, which can contain useful information about problems such as national intelligence, cyber security, fraud detection, marketing, and medical informatics. Companies such as Google and Microsoft are analyzing large volumes of data for business analysis and decisions, impacting existing and future technology.

A. Machine learning on big data

Machine learning (ML) is continuously unleashing its power in a wide range of applications. Big data enables ML algorithms to uncover more fine-grained patterns and make more timely and accurate predictions than ever before; on the other hand, it presents major challenges to ML such as model scalability and distributed computer. Artificial neural network (ANN) is one of the ML algorithm to process the data from the big data storage. The big data use tool to give

the detail information from raw data to the ANN classification. So that the ANN quickly process the data and classify the informations.

B. Significance in Contribution

Especially, nowadays no countries, no communities, and no person are immune to urban emergency events. Detection about urban emergency events, e.g., fires, storms, traffic jams is of great importance to protect the security of humans. Eventhough, many technology has been developed in country but there is no technology to convey the immediate emergency events to people and only the description about the event are post to social media after the events occur long time. This system is to fuse Artificial Neural Network (ANN) for filtering irrelevant information, alarming of urban emergency events in multimodel quickly and for better accuracy.

II. RELATED WORKS

A. Event detection

KehuaGuo et. al (2017) First, using the CSF algothim the correlation of cross-modal semantics are mined .Semantic informations from the heterogeneous multimedia may be orginate from sensor, mobile device, web pages, user generated data and the semantic objects are normalized for fusion. Second, we employ the dimension reduction and relevance noise are reduced. Finally, we research the storage and distribution mechanism e.g. Hbaseapproach. First, given the heterogeneity of media documents obtained on the Internet, we provided a convenient interface for users to extract semantic information. Second, given the heterogeneity of the semantic objects, we designed algorithms to perform normalization and fusion. Use machine learning than CSF algorithm for fast update.

Matthias Moi et.al (2016) Huge volume of low-quality messages will be continuously gathered from a variety of social media services such as Facebook or Twitter. Our aim is to design a software system that will process and analyze social media data, transforming the high volume of noisy data into a low volume of rich content that is useful to emergency personnel. Therefore, suitable techniques are needed to extract and condense key information from raw social media data, allowing detection of relevant events and generation of alerts pertinent to emergency personnel. aim is to design a software system that will process and analyze social media data, transforming the high volume of noisy data into a low volume of rich content that is useful to emergency personnel. Therefore, suitable techniques are needed to extract and condense key information from raw social media data, allowing detection of relevant events and generation of alerts pertinent to emergency personnel. Using the naive bayes classifier for accuracy. Data scarcity due to

naive bayes, the events are not fully mentioned Use service oriented architecture principle for better result.

Takeshi Sakakiet. al (2016) Twitter has received much attention recently. An important characteristic of Twitter is its real-time nature. We investigate the real-time interaction of events such as earthquakes in Twitter and propose an algorithm to monitor tweets and to detect a target event. To detect a target event, we devise a classifier of tweets based on features such as the keywords in a tweet, the number of words, and their context. Subsequently, we produce a probabilistic spatiotemporal model for the target event that can find the centre of the event location. First, we crawl numerous tweets related to target events; second, we propose probabilistic models to extract events from those tweets and estimate locations of events; finally, we developed an earthquake reporting system that extracts earthquakes from Twitter and sends a message to registered users. Svmclassifier used to classify the target event words. Produce awareness to people and develope event reporting system By using of probabilistic model, we need to give the rank to the word and Accuracy is less.

B. Social Media datas

YimingGu et. al (2016) Develop a methodology to translate tweets into traffic incident information. We conduct the initial data acquisition from Twitter servers, followed by an iterative process, namely the adaptive data acquisition where we crawl tweets and establish our dictionary of “words” relevant to traffic incidents. The process of adaptive data acquisition also selects the most important features to form a feature space that is informative and non-redundant. Next, tweets are mapped into this feature space and classified by a well-trained Semi-Naive-Bayes (SNB) classifier as either TI or NTI tweets. All the TI tweets are then pushed through a geo-parser and geocoder, to determine their locations. In addition, each TI tweet is further classified by a trained Supervised Latent Dirichlet Allocation classifier to identify the category of the incident it reports. Geocoder contains the additional names of roads and points of interests with the capacity to correct misspelled names. The data acquisition is limited by the maximum no. of tweets. Misspelled names leads to negative result.

Guandan Chen et.al (2017) EAS has the ability to aggregate emergency information from CCTV devices. Steps involved in alerting emergency services such as the fire/police station to an emergency situation. CCTV stores the captured video data in their own storage device. The analyzer module periodically monitors the stored video data based on the deep-learning technology, using heuristic/knowledge-based machinelearning technology,. When the system detects disaster, it sends an emergency alert message directly to the fire/police station. Fire department/police station receives the emergency alert message accompanied by other related information such as location, type of disaster, analyzed results, and image data

(optional). to avoid network congestion, the system optionally sends the image files. The main advantage of the proposed system is that it does not require additional devices or infrastructure. Deep-learning-based real-time video analyzing module inside the CCTV device. Our system uses computer simulation to immediately detect accidents and natural disasters. It is not high secure data.

Guandan Chen et. al (2017) an online event detection and tracking method based on similarity metric learning using neural network. Our method first trains a classification model to identify event related texts. To detect and track events, we adopt a clustering-based approach. Specifically, we use neural network to jointly learn a similarity metric and low dimension representation of events, and then use a memory module to store and update event representation. To solve this problem, clustering based methods cluster words using frequency and content similarity. The event representation is weighting sum of the vector representations of related tweets. We use a memory module to store and update representations of events. Neural network training is not well sufficient take too much of time to classify the events.

C. Sensor Datas

Motiwaleet. al (2017) A challenge with these sensors is filtering the raw data to include authentic impacts and exclude false events that are sometimes registered due to the sensitivity of the sensors. In this study we have developed an algorithm based on artificial neural networks and discrete Fourier transform based filtering that will be used to distinguish between a biomechanically relevant event and a non-impact transient which is of no concern. Using this approach we report a specificity of 47% and a sensitivity of 88% in the ability to distinguish between real impacts and non-impact transients. There are hopes that these sensors may provide valuable information related to dangerous, possibly injury-inducing impacts that may cause concussions, or traumatic brain injuries (TBIs). The raw data is uploaded by the sensor from the field to Amazon encrypted cloud services. This raw data is first pre-processed and then sent to two layers of filters, namely, neural network and DFT filter, simultaneously. The results from these two layers are then combined in parallel. Feature selection is an important step for neural network algorithms to determine the best form of input that should be given to it. The main challenge that the sensor technology faces today is not data collection, but developing intelligent algorithms which can classify this data meaningfully to extract scientifically and clinically relevant information.

III. PROPOSED MODEL

Detection about urban emergency events is of great importance to protect the security of humans. The objective is to detect the urban emergency event in crowdsourcing. Crowdsourcing is a process of acquisition, integration, and analysis of big and heterogeneous data generated by a

diversity of sources in urban spaces, such as devices, vehicles, buildings, and human.

The data generated by the IoT camera are stored in the big data because the non-traditional strategies and technologies needed to gather, organize, process, and gather insights from large datasets. In order to describe the real time urban emergency event, the 5W (What, Where, When, Who, and Why) model is proposed. Big data enables Machine learning algorithms to uncover more fine-grained patterns and make more timely and accurate predictions than ever before; on the other hand, it presents major challenges to ML such as model scalability and distributed computer. Artificial neural network (ANN) is one of the ML algorithm to process the data from the big data storage. The big data use tool to give the detail information from raw data to the ANN classification. Artificial neural network are help to classify the correct events and deliver to the social media. The ANN process has the input layer, hidden layer and output layer. ANN filter the irrelevant information and deliver the multimodel information about the events quickly and accurately.

The proposed system is to use Artificial Neural Network for filtering irrelevant information, alarming of event efficiently and for better accuracy. The consequence of this system to develop alarming of Multimodel urban emergency events in crowdsourcing to social media.

A. Data Organisation

Load the crowd place data information and social media data to database. The crowd place data there are many types of attributes are involving for e.g. (Place name, Place Id, Place Location, Latitude, Longitude etc.) this data may store into the database. And next we load the Social media Dataset in this dataset (Social people id, photos, shares, time, likes etc.) may attributes are involve. This is the public dataset list are stored in the database. IoT camera monitor the crowd place information and store it in the big data using HDFS map reduce. The information about each camera in the database. The attribute to the each camera are set by the admin

ID	Sensor	County	name	latitude	longitude	area	temperature	pressure	acceleration	wind
1	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
2	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
3	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
4	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
5	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
6	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
7	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
8	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
9	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
10	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
11	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
12	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
13	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
14	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
15	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
16	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
17	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
18	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
19	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0
20	36	America	California	34.0522	-118.2437	San Diego	72.0	1013.25	0.0	0.0

Organization of data

Randomized Fixed Control Algorithm:

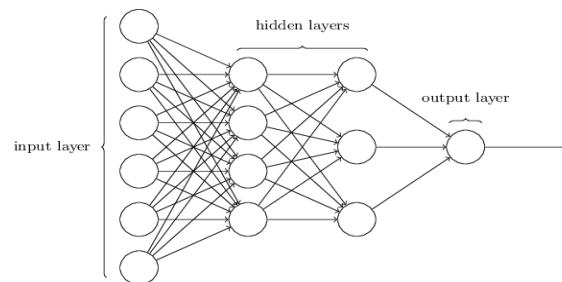
Machine learning process is fuse in IoTserver, the data in the IoT server are classified using the ANN classification. This ANN classifies the event data by normal and abnormal conditions. ANN is used as a random function approximation tool. These types of tools help estimate the most cost-effective and ideal methods for arriving at solutions while defining computing functions or distributions in figure. ANN takes data samples rather than entire data sets to arrive at solutions, which saves both time and money. ANN have three layers that are interconnected. The first layer consists of input neurons. Those neurons send data on to the second layer, which in turn sends the output neurons to the third layer.

```

graph LR
    Max[Maximum Value] --> MM[Max-Min=Value]
    Min[Minimum Value] --> VG[Value Generation]
    MM --> FC[Fixed Counting]
    FC --> VU[Value Updated]
    VU --> VG
    VG --> MM
    subgraph Process
        MM
        FC
        VU
        VG
    end
    Process --> Out[Output]
  
```

Formulation of neural network

An ANN is based on a collection of connected units or nodes called artificial neurons (a simplified version of biological neurons in an animal brain). Each connection (a simplified version of a synapse) between artificial neurons can transmit a signal from one to another. The artificial neuron that receives the signal can process it and then signal artificial neurons connected to it.

[illegible]

```

graph TD
    subgraph Data_organisation [Data organisation]
        CP[Crowd place] --> CPD[Crowd place data]
        SM[Social media data] --> DB[(Database)]
        CPD -- Monitoring place --> IOTC[IOT camera]
        IOTC --> DB
    end

    subgraph Big_data_process [Big data process]
        DB --> MR[Map reduce]
        MR -- Formatted data --> IOTS[IOT server]
    end

    subgraph Event_classification [Event classification]
        IOTS --> ANN[ANN classifier]
        ANN --> AN[Alert notification]
        AN --> S[Server]
        S --> SM2((SOCIAL MEDIA))
        SM2 --> DB
    end

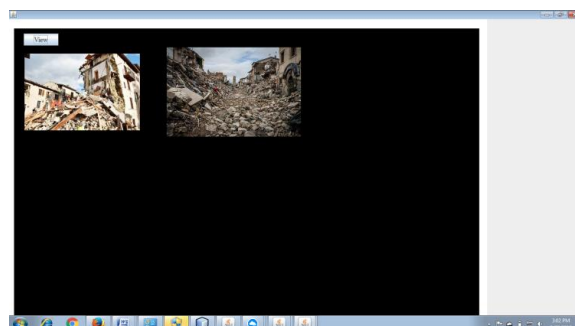
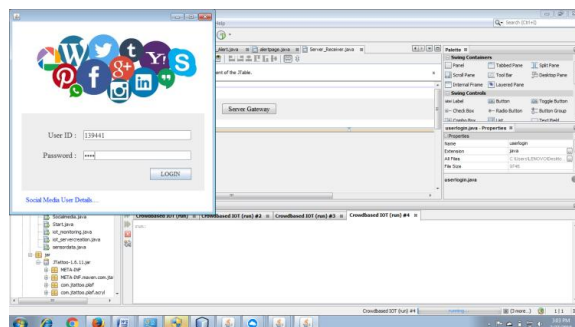
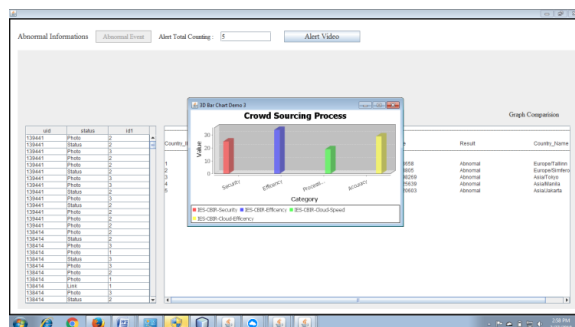
    AN -- "Classifies events  
normal" --> S

```

Proposed system Architecture

D. Alert Notification

The information from the server is abnormal the alert notification send to the social media user via ANN process in the form of multimodal description. The sensing data from volunteer contributors such as social network users can be further analysed and processed, and leveraged in many areas such as environment monitoring, urban planning, emergency management, .



Alert notification

IV.CONCLUSION

Emergency event is one of the main problem in large crowdsourcing area. The events are not immediately deliver to the social media. The existing system has lot of limitation and challenges. This system tie with Artificial neural network with big data for irrelevant post filtering and post the information accurately to the social media users. The results show the efficiency to Improve urban environment, human life quality, and city operation systems and public safety and health.

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