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Federated Learning-Driven Threat Detection in Blockchain-Based Industrial IoT: The BlockHunter Framework

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ABSTRACT

One of the most talked-about activities on social media is the dissemination of information about the latest natural or man-made catastrophes. Key responsibilities in this domain include the immediate detection of critical needs, the rapid dissemination of relevant information, and the rapid reaction to those needs. Using social media as a central component, this study aims to create a solution for crisis administration and emergency reaction. This method employs text analysis techniques to refine the process by which officials respond to emergencies and sift information collected automatically to aid in rescue efforts. To facilitate a swift response in an emergency, we employed cutting-edge methods in the fields of Machine Learning (ML), Deep Learning (DL), and Natural Language Processing (NLP) based on supervised and unsupervised learning with social media datasets. The blockchain infrastructure is used in this process to verify the trustworthiness of the events that have been identified and to remove the need for a central authority. The combined system is used to increase security and openness so that false information about an event is not spread on social media.

Keywords

deep learning, machine learning, NLP, bitcoin, and event recognition.

INTRODUCTION

In the past few years, disasters have become routinely reported on in the social media news cycle. Natural disasters, such as earthquakes, floods, and typhoons, and man-made disasters, such as acts of terrorism and industrial mishaps, are just two examples [1]-[3]. With millions of people using the internet every day, it's no surprise that the number of social media networks and the volume of their everyday activity are both rapidly expanding [4]. Daily events and stories are prevalent in user-generated material because they are what people are talking about right now. Online communities provide a robust setting for people to share and receive information about a wide range of topics and activities. Early event recognition and monitoring presents a unique challenge in the context of social networking and information sharing during emergency situations and potentially catastrophic events. Recent developments in connectivity and the proliferation of social media have opened the door to crisis management through crowdsourcing. Ushahidi [5] is one of the most well-known.

crowdsourcing tools, and its ability to show crowd-sourced data serves as a perfect illustration of how this methodology can be used to raise consciousness across a variety of social networks. National security agencies, media sources, civic defines organizations, etc. are just a few examples of the many channels available for disseminating information about current events. During this time of need for improved disaster management, the full potential of social media became apparent. Micro-blogging, which is a dynamic subject due to its acronyms, casual language, character limit, etc., is the degree of the restricted generalization cause. Recent innovative approaches to Twitter spotting have been suggested by Kruse et al. [6] using a segmentation technique, and by Fedrizzi et al. [7] using a complete Twitter firehose to demonstrate the spatial relevance of tweets.

WORK IN RELATION

Converging the physical and digital worlds, IoT and blockchain powered by machine learning have recently ushered in a monumental revolution across many industries, most notably healthcare [8]–[13], navigation [14–16], security [17–21], cloud computing [22], and smart grid systems [23]. In this part, we examine the different social media platforms that collect crisis-related data to assist disaster-related activities. To achieve a more precise and rapid design for the e-commerce system, Hui-Jia Li et al. [24] suggested the optimization method based on dynamical clustering. Another method used by this author [25] to try and address the issue of effective community discovery identifying was based on the application of an optimization technique. Using a dynamic method on a signed network, Hui-Jia Li et al. [26] suggested a remedy for the epidemic spread issue.

DISASTER CYCLE MANAGEMENT

The phases of a disaster can be broken down into four distinct phases: prevention, protection,

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reaction, and clean-up. The stages of preparation and prevention occur before the catastrophe's impacts, and the other two occur after the disaster has occurred. The forethought and planning that lessens the blow of an occurrence. Preparations for impending events are kicked off in response to social media alerts. The immediate fallout of a catastrophe is caused by the reaction that is made during an emergency situation. Conspicuous in ML systems is the ability to separate the tweets with helpful contents linked to catastrophes, which is used for the balance of active emergency during the reaction phase. The roles of social media during a catastrophe are outlined in Table 1.

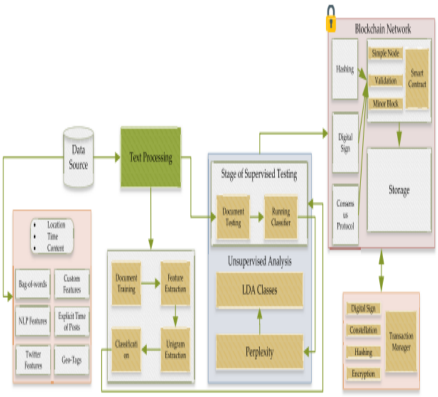

FIGURE 1. Overview of supervised and unsupervised analysis in crisis event detection based on blockchain.

SOCIAL MEDIA AND CRISIS MANAGEMENT ANALYTICS POWERED EVENT DETECTION APPROACH

The primary goal of this system is to establish a social media disaster management setting in the cloud. The central argument presented

TABLE 2. Comparison of related researches to event detection.

Author	Proposed Approach	Advantages
Yuwei et al. (2021) [29]	Novel knowledge preserving incremental heterogeneous graph neural network	Extracting the unseen information from shared contents in social media
Habib et al. (2021) [30]	Novel dynamic crowd video modeling for event detection	Improving the performance system based on limited multi-frame data
Heinrich et al. (2021) [31]	Sound event detection based on triple threshold	Improve the performance of segmented localized event level
Lida et al. (2021) [32]	Social media emergency event detection based on similarity between contents	Clustering the textual contents regarding the 3w attributes.
Akash et al. [33] (2021)	Blockchain-based event-driven for the decentralized market place	Effecting on the specifications of event based on the flexible requirement.
Ebtesam et al. [34] (2021)	Blockchain-based event detection from road traffic social sensing	Extracting the validate events without need of prior knowledge from twitter media.
Proposed Approach	Blockchain-based event detection for the shared information related to crisis	Improving the performance of system in term of security and transparency and predictive analysis of textual dataset.

integrating social media's capacity to maintain the human monitor in the public eye with existing sensor-based Disaster Risk Management (DRM) systems. By employing semantic analysis to generate action and content-based replies, this process initiates the power of the relevant crisis management. The data gathered can be used for early notification, risk reduction, and impact evaluations in emergency situations and catastrophe management. The basic framework for spotting events in social media is depicted in Figure 2. Event recognition, automated logic, incident monitoring, and cryptocurrency are the four cornerstones of this framework. Social network data collected in real time is used for incident detection. Using sophisticated methods, automatic reasoning draws relevant information and insights from publicly available data. Monitoring incidents, dealing with knowledge-based professional emergencies via sense interfaces, and analysing the system's security, openness, and proof-of-authority via blockchain technology. The following sections elaborate on each individual part.

NATURAL LANGUAGE PROCESSING FOR INCIDENT DETECTION

In this part, we'll go over the major features of the natural language processing technique that was used. Natural language processing (NLP) is a well-known method for gaining insights from texts. Real-time updates on global events are widely disseminated through social media in the form of messages and comments. Here are some definitions for the three major parts of this scheme.

IDENTIFICATION AND EVENT REPRESENTATION

Depending on the user, event recognition can be set off either immediately or manually. Crawling data should be governed by a set of rules. A location-

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based scraper requires a specific social media network setup, a specific frame size, and a specific target region. It is necessary to specify particular search terms or pre-defined terms in the database to find the keywords, and the position pinpoint gives the information linked to a place using the Google API. The algorithm uses this information to look for similar articles and content in an effort to identify material written in multiple languages. To accomplish this, the language translation service relied on APIs from Google and Microsoft to transform the contents into the target language and store them in a library of knowledge-based, unique terms. After the parameters have been established, the system will begin scraping data from the various social media sites. Stories, comments, pictures, texts, videos, locations, and more can be found in every single one. Crawled data was formatted properly so that it could undergo pre-processing and lexical analysis. The frequency with which particular occurrences occur in widely disseminated materials is displayed in Equations 1 and 2 [41]. Terms in document t are represented by w, and the class of unknown variables is represented by a.

$$X(w,t) = 1 + log_{10} \quad (1)$$

$$X(t,w) = X(t)\sum_{a} X(w|a)X(a|t) \quad (2)$$

EVENT-BASED PREDICTIVE ANALYSIS

Here, we apply predictive analysis to the event recognition process in an effort to boost the system's efficiency and verify the usefulness of the feedback it generates. In a similar vein, the accessible

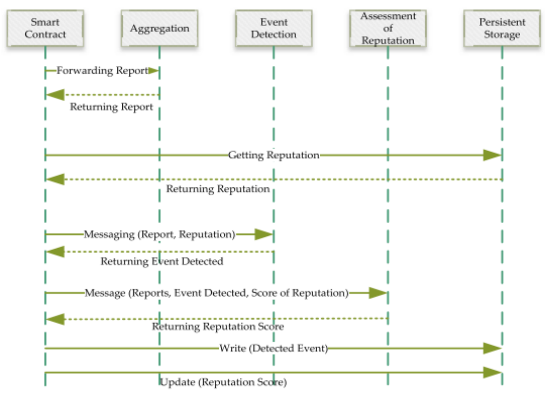

FIGURE 2. Relationship between persistent storage and smart contract in event detection.

The information used in this procedure has been thoroughly examined.

EDUCATION OF PREDICTION MODELS

There are two main parts to the forecasting model used here: the learning module and the prediction algorithm. The forecast model's past data is typically used as a "training set," or a group of examples to learn from, and to uncover underlying relationships and trends in the input and output variables. The next phase involves making an educated guess based on the raw data provided by the user for the training model. The accuracy of the forecast algorithm is conditional on meeting certain criteria. All prediction algorithms fall short when it comes to dynamically training input states, even though the training data and the input data application situations are identical. So, in Figure 4, we showed the results of our learning forecast models. Here, we use the learning module to fine-tune the prediction method and boost the precision of the prediction model. The exterior factors that are a part of the learning module are closely tracked by the system as it measures the success of the forecast algorithm. Learning module can update adjustable parameters of prediction algorithm and improve performance by switching from train model to prediction algorithm based on ambient tiggers observed after investigating external variables and prediction model outputs. The implemented method optimizes the system's efficiency and precision through the application of a learning component.

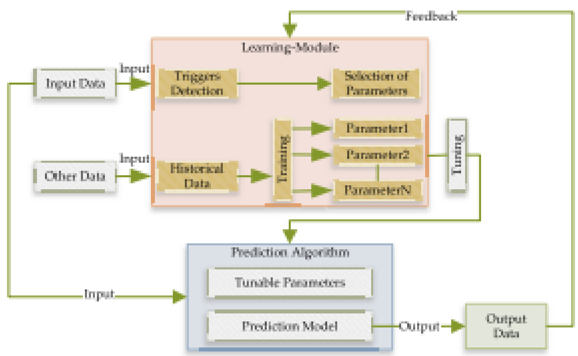

FIGURE 3. Event detection conceptual view for predictive model learning.

The learning module checks the performance of the system continuously based on getting feed-back as output.

RESULTS AND IMPLEMENTATION OF THE PROPOSED EVENT DETECTION

This section presents the results of the applied deep learning algorithm of the contents collected from Twitter shared Informotion and platform and analysed the proposed approach compared with other existing works in this area.

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DEVELOPMENT ENVIRONMENT AND EXPERIMENTAL EVALUATION

The development environment of implementing the proposed event detection system summarized in Table 3. In total, there

TABLE 3. Development environment.

Module	Component	Description
Predictive Analysis Model	Operating System	Microsoft Windows 10
	CPU	Intel(R) Core(TM) i7-8700@3.20GHz
	Main Memory	16GB RAM
	Core Programming Language	Python
	IDE	PyCharm Professional 2020
	ML Algorithm	Deep Learning
Web Application	Operating System	Windows 10
	Browser	Chrome, Firefox, IE
	Programming Language	HTML, JavaScript
	Library/Framework	Notify.js
Blockchain Framework	Operating System	Ubuntu Linux 18.04 LTS
	Docker Engine	Version 18.06.1-ce
	Docker Composer	Version 1.13.0
	IDE	Composer Playground
	Programming Language	Node.js

are six primary elements at play here, including the operating system (Microsoft Windows 10) and central processor unit (CPU; Intel(R) Core(TM) i7-8700 @3.20GHz). The machine is currently making use of 16GB of RAM. Python is the primary language, and PyCharm Professional 2020 is the integrated development environment (IDE) and deep learning model.

THE CURRENTLY AVAILABLE DATASET AND ANALYSIS FOR EVENT DETECTION

One of the most crucial parts of knowledge-based systems is collecting data from social media during a disaster so that a system can be built around the requirements of its users. From what we can tell, Twitter posts offer the best combination of specificity and accessibility. The collection of accessible Twitter material databases during crisis and catastrophe events is provided in Table 4. This collection is defined by its data format, the number of messages it contains, and the number of occurrences it tracks. Figure 5 depicts the data modelling procedure for incident detection with regards to incident reporting, information sources, and credibility. Seven machine learning methods were applied to the data, and the results were compared to the deep learning model used in this system, as shown in Figure 6. Naive Bayes, K-Nearest Neighbour, SVM, LR, LRX, Boost, and Deep Learning are the methods available. The COVID19 collection has associated groups. The results demonstrate that the proposed method outperforms competing algorithms across the board.

TWEET CATEGORIZATION

Classifying social media posts and material into humanitarian groups helps to better catch the events and locations that are being discussed. Table 5 summarizes the method of classifying nearly 2,000 tweets into nine distinct groups. To train the specified model, we use 90% of the aggregated articles for training and 10% for testing. Table 5 displays the percentage of categorized tweets that fall into multiple humanetrain classifications. Contents that are unrelated to the stated are presented in the unimportant group.

TABLE 4. Data collected during times of crisis.

Data	No. Tweets	Events
GeoCov19 [45]	524.000.000 From May 2020	COVID19
covid19_twitter [46]	400.000.000 Mid June 2020	COVID19
Kaggle covid19 [47]	1.500.000 1st May 2020	COVID19
Appen Disaster Response Messages [48]	30.000	Earthquake, Flood, Hurricane
TREC-IS 2019A [49]	30.000	Bombing, Earthquake, Flood, Typhoon, Wildfire, Shooting
Disaster Tweet Corpus 2020 [50]	150.000	Earthquake, Flood, Biological, Hurricane, Wildfires, ...
Florence [51]	600.000	Hurricane
Epic [52]	25.000	Hurricane
Crisis MMD [53]	16.000	Hurricane, Hurricane, Flood, Typhoone, ...
CrisisLexT26 [54]	26.000	Earthquake, Flood, Wildfire, Meteor, Typhoon, ...
Events 2012 [55]	150.000	Disasters and accidents

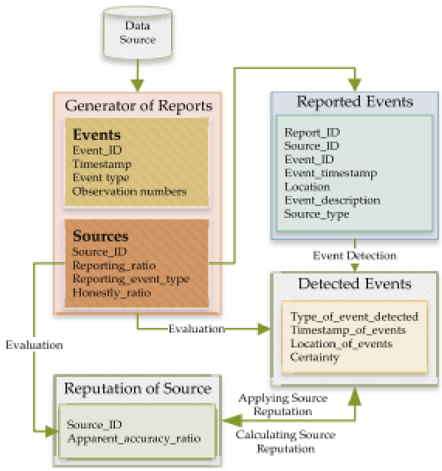

FIGURE 4. Event detection reports and reputation source assessment in the data model.

subject the material of this section is linked to government regulations. The accounts of how many people are being impacted by this illness are the basis for the effect materials. The papers include data on the total number of deaths and impacted individuals.

FURTHER STUDY AND DISCUSSION

This system's presentation of a blockchain and machine learning workflow is a major step toward guiding future research. In the future, we can adapt this procedure to work with a wide variety of networks and catastrophe types. It's possible that the process will be weakened across all catastrophes due to the lack of wide relief aid. By combining different forms of artificial intelligence, we can gain insight into a wide range of phenomena, including the regions hit by a catastrophe, the messages and information being shared, and the additional material that can be used to bolster the system. The system's consciousness can be raised through the incorporation of data from a variety of sources.

CONCLUSION

In order to autonomously connect crises and catastrophes with different aid groups assisting the rescue efforts, the system demonstrated here is built on the blockchain and a machine learning workflow. Event recognition, categorization, mapping contents using different humanitarian categories, grouping, and confidence verification are the specified pipeline's subcategories. Case study of data from Twitter and social media platforms is represented by the networks displayed. The findings boil down to components for improving system efficiency and preventing the spread of false information, as well as for forecasting and learning about new subjects.

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