International Journal of Scientific Research in Science, Engineering and Technology
Print ISSN - 2395-1990
Online ISSN : 2394-4099
Available Online at : www.ijsrset.com
doi : https://doi.org/10.32628/IJSRSET2310611

Active online Multiple Prototype Classifier to Support Crisis Management

Vankipuram Lavanya, Dr. D. Shobha Rani
Department of Computer Science and Engineering, Chadalawada Ramanamma Engineering College, Tirupati, Andhra Pradesh, India

ARTICLEINFO

Article History :

Accepted: 10 Nov 2023
Published: 30 Nov 2023

Publication Issue :
Volume 10, Issue 6
November-December-2023
Page Number :
267-277

ABSTRACT

In times of crisis, social networks have emerged as crucial channels for open communication. The traditional methods employed for analysing social media data in crisis situations have faced criticism due to their mixed results and limited applicability beyond the scope of the initial study. To address these issues, a novel online active multi-prototype classifier, known as AOMPC, has been proposed. AOMPC operates with data streams and incorporates active learning mechanisms to actively request labels for unlabeled and ambiguous data points, managing the number of requests through a fixed budget strategy. Typically, AOMPC is designed to handle partially labelled data streams. To assess its effectiveness, AOMPC was evaluated using two types of data: synthetic data and Twitter data related to two specific crises—the Colorado floods and the Australian wildfires. During the evaluation, established parameters were utilized to gauge the quality of results, and a sensitivity analysis was conducted to understand how AOMPC's parameters impacted result accuracy. Furthermore, a comparative study was carried out to contrast AOMPC with other available e-learning algorithms. The experiments demonstrated AOMPC's capability to perform exceptionally well in processing partially labelled scalable data streams, potentially offering valuable insights during crises.

Keywords : AOMPC, Support Crisis Management, Social Media, Sensitivity Analysis, Machine Learning

I. INTRODUCTION

The primary objective of crisis management involves a series of actions to be taken before, during, and after a crisis occurs, including prevention, preparedness, response, recovery, and mitigation. To efficiently execute these tasks, leveraging data from various sources, including the public's observations of emergency events, is essential. Such data can empower emergency operations centers to coordinate rescue and response efforts effectively. In recent years, numerous research studies have explored the utility of social media (SM) as a valuable source of information for enhancing crisis management. Notable case studies, including the Norway Attacks, Minneapolis Bridge Collapse, California Wildfires, Colorado Floods, and Australia Bushfires, have exemplified the significance of SM data [1]. The widespread use of SM has prompted a reevaluation of public engagement in crisis management, given the new technologies and opportunities it presents.

Previous research on SM in emergency response has focused on both offline and online clustering of SM messages. Offline clustering was employed to retrospectively identify sub-events or specific hotspots from SM data during a crisis, enabling post-event analysis [2]. Online clustering on the other hand identified evolving sub-events in real-time with mechanisms for online feature selection to continuously and incrementally accommodate SM data streams. Notably, emergency departments, such as police forces, have already adopted SM for gathering, monitoring, and disseminating information to inform the public.

In response to these developments, the authors propose an active learning algorithm, AOMPC, which relies on user feedback to label and classify items being processed. AOMPC serves as a filtering mechanism to distinguish valuable information from irrelevant content in user-generated SM [3]. The primary goal is classification, with the classifier's role being to identify important SM items related to the crisis event with the user's guidance. These selected items serve as cues for identifying sub-events, which are distinct topics commonly discussed during a crisis (e.g., flooding, bridge collapses in specific areas). Sub-events are recognized by aggregating SM messages describing the same topic. The authors propose an approach akin to Learning Vector Quantization (LVQ) for multiple prototype classification to create the AOMPC classifier [4]. This classifier operates online to handle the continuous stream of data, employing both labeled and unlabeled data, with active learning to tag ambiguous data items. The number of user queries is controlled by a predetermined budget, enhancing the AOMPC classifier's ability to discriminate and classify relevant information. While AOMPC is adaptable to various streaming data applications, the authors particularly focus on its relevance to SM data analysis [5].

The paper offers several significant contributions, which are summarized as follows:

1. Introduction of AOMPC: The paper introduces a novel online learning algorithm known as AOMPC, which is designed to efficiently handle data streams. This algorithm is inspired by previous work and incorporates a multi-prototype approach with similarities to Learning Vector Quantization (LVQ).
2. Active Learning Strategy: AOMPC incorporates an active learning strategy to enhance its classification capabilities and, specifically in this paper, to facilitate sub-event detection. This strategy utilizes concepts of budget and uncertainty to determine when and what data should be labeled, thereby improving the algorithm's performance.
3. Diverse Dataset Evaluation: AOMPC's effectiveness is assessed using a variety of data sources, including synthetic datasets (numerical data and geo-tagged micro blogs) and real-world datasets collected from Twitter. These real-world datasets pertain to two distinct crises: the 2013 Colorado Floods and the 2013 Australia Bushfires. The choice of these datasets is motivated by their diversity, allowing for a comprehensive evaluation of AOMPC due to their differing characteristics.
4. Sensitivity Analysis: The paper conducts a sensitivity analysis that explores the impact of various AOMPC parameters on its performance. This analysis provides insights into how parameter settings influence the algorithm's results.
5. Comparison with Other Algorithms: A comparative study is carried out to assess AOMPC's performance in comparison to well-known online algorithms. The findings of this comparison are discussed, shedding

light on AOMPC's strengths and weaknesses relative to existing algorithms.

In summary, the paper's contributions encompass the development of AOMPC as an online learning algorithm with active learning capabilities, its evaluation using diverse datasets from both synthetic and real-world sources, a sensitivity analysis of its parameters, and a comparison with other online algorithms to provide a comprehensive understanding of its utility and performance in the context of crisis management and data stream processing.

II. RELATED WORKS

A. Data Mining and Machine Learning

The introduction provides an overview of prototype-based models in supervised machine learning. These models revolve around the core concept of representing previously observed data through "prototypes," which serve as typical representations of the data's key properties. By employing an appropriate distance or dissimilarity measure, these prototypes can be utilized for the classification of intricate, potentially high-dimensional data [6]. The introduction uses the well-known Learning Vector Quantization (LVQ) as an illustrative example, frequently utilizing the standard Euclidean distance measure.

The advantages of prototype-based models are highlighted. They are prized for their transparency and intuitiveness, making them stands out from more complex, black-box systems. The process of extracting information from existing data, as well as comparing new data to prototypes using a suitable distance measure, is straightforward [7]. Prototype-based models are frequently applied in unsupervised analysis tasks, focusing on revealing underlying data structures like clusters or hierarchical relationships.

The introduction further mentions the use of prototype-based models in unsupervised learning, where they are employed for tasks such as clustering and the identification of data patterns [8]. Competitive Vector Quantization and the widely recognized K-means algorithms are cited as notable examples in this context.

In the realm of supervised machine learning, the primary goals include categorizing data into classes for classification tasks or characterizing them with continuous values in regression problems. Achieving these objectives relies on having labeled example data for training. During training, the aim is to extract pertinent information from the labeled data and formulate a hypothesis that represents the unknown target function [9]. This hypothesis can then be applied to new, unlabeled data during the operational phase. Prototype-based models offer a promising approach to tackle these supervised learning challenges effectively.

B. Learning Similarity Metrics for Event Identification in Social Media

The provided text discusses the significance of social media sites, such as Flickr, YouTube, and Facebook, as platforms for users to share their experiences and interests on the web. These platforms host vast amounts of user-generated content, including photos, videos, and textual material, covering a wide range of real-world events of varying types and sizes [10]. The central focus of the paper is to automatically identify these events and the associated user-contributed social media documents. Achieving this can enable event browsing and enhance the capabilities of state-of-the-art search engines.

To tackle this challenge, the authors leverage the rich "context" linked with social media content. This context comprises user-provided annotations like titles and tags, as well as automatically generated information such as the content creation time. By utilizing this extensive contextual information, encompassing text and non-text features, the paper defines suitable document similarity metrics to facilitate online clustering of media into events [11]. Notably, the paper explores various techniques for learning multi-feature similarity metrics in a principled manner, which is a key contribution.

The paper's evaluation is conducted on large-scale real-world datasets of event images sourced from Flickr [12]. The results of the evaluation suggest that the approach presented in the paper is more effective in identifying events and their associated social media documents compared to the existing state-of-the-art strategies upon which it builds.

The paper underscores the increasing volume of content related to real-world events being shared on social media sites like Flickr, YouTube, and Facebook. These events encompass a wide spectrum, from widely recognized occurrences like presidential inaugurations to smaller, community-specific events like annual conventions and local gatherings [13]. The automatic identification of these events and their associated social media content is seen as a means to empower local event browsing and search, complementing and enhancing the local search tools provided by web search engines.

In summary, the paper addresses the challenge of identifying events and their associated user-contributed content on social media platforms [14]. It emphasizes the potential value of this approach for individuals seeking information about specific events and highlights the limitations of traditional web search results for lesser-known events.

C. Multiple-Prototype Classifier Design

The paragraph describes a study involving the review and comparison of five existing methods for generating multiple prototypes from labeled data. It then introduces a novel approach, which is a modification of Chang's method, as a sixth method [15]. The primary objective is to compare these six methods with two standard classifier designs: the 1-nearest prototype (1-np) and 1-nearest neighbor (1-nn) rules.

The basis for comparing these methods is the reconstitution error rate, and the data used for the evaluation are the Iris data. Among the six methods, the modified Chang's method consistently produces the best design with zero errors, indicating its effectiveness in classification. Additionally, one of the competitive learning models yields the best minimal prototype design, with just five prototypes resulting in three reconstitution errors [16].

In summary, this study focuses on prototype generation from labeled data and evaluates various methods, including the introduction of a modified version of Chang's method [17]. The performance of these methods is compared against standard classifier designs using the Iris data, and the results suggest the superiority of the modified Chang's method in achieving zero errors in classification.

III. SYSTEM ANALYSIS

A. Existing system

The previous work on social media (SM) in emergency response had a dual focus on both offline and online clustering of SM messages.

1. Offline Clustering: The offline clustering approach was employed to identify sub-events, which are specific hotspots or noteworthy occurrences, from the SM data related to a crisis. This offline clustering was primarily intended for conducting after-the-fact analysis [18]. It allowed for the retrospective examination of SM data to uncover significant sub-events that transpired during the crisis.
2. Online Clustering: In contrast, the online clustering method was geared towards identifying sub-events that evolve dynamically over time. It focused on real-time tracking and recognition of sub-events as they developed during the crisis. Notably, online feature selection mechanisms were developed to support this approach. These mechanisms facilitated the continuous and incremental accommodation of SM data streams, enabling the system to adapt to the evolving nature of crisis-related information on social media platforms [19].

In essence, the combination of offline and online clustering techniques, along with online feature selection, aimed to provide a comprehensive and timely understanding of crisis-related events and developments as they unfolded on social media.

Disadvantages: Due to the fact that SM data is noisy, it is important to identify relevant SM items for the crisis situation at hand. The idea is to find an algorithm that performs this classification and also handles ambiguous items in a reasonable way. Ambiguous denotes items where a clear classification is not possible based on the current knowledge of the classifier.

B. **Proposed System**

The provided text highlights an interesting observation: individuals within emergency departments, including entities like police forces, are already leveraging social media (SM) platforms for various purposes. Specifically, they use SM to collect, monitor, and distribute information to keep the public informed during emergency situations.

In response to this observation, the authors propose a learning algorithm known as AOMPC [20]. AOMPC is designed to facilitate active learning, and it relies on user feedback obtained through queries during the processing of items. As AOMPC is a classifier, these queries are directly related to the labeling of the items being processed. This approach allows the algorithm to harness the knowledge and insights of users, particularly those in emergency departments, to enhance its classification and decision-making capabilities.

In essence, AOMPC aims to harness the expertise and feedback from users, including professionals in emergency response, to improve the accuracy and effectiveness of its classification and decision-making processes when dealing with SM data.

Algorithm 1 relies on the computation of the distance between the input and the existing prototypes because the SM items usually consist of a textual description (c.f., tweets), we apply the Jaccard coefficient [21] as a text-based distance (dist text). If the social media items consist of two parts, the body of the message and the geo-location that indicates where the message was issued in terms of coordinates, then we apply a combined distance measure (dist text+dist geo)/2. Specifically, dist text refers to the Jaccard coefficient, while dist geo is the Haversine distance [13], [5] described in Algorithm 1, steps 4-7. The coordinates are expressed in terms of latitude and longitude. Moreover steps 4-12 of Algorithm 1 are related to the active learning part. The algorithm starts by checking whether the new input item lies in the uncertainty region between the relevant and irrelevant prototypes and whether there are enough budgets for labeling this item. More details follow in the next section.

Algorithm 1: Steps of AOMPC

Input: Data stream X

Output: List of prototypes V

1: CT=1; LTU=CT;

2: Let CT and LTU indicate the current time and the last time a prototype was updated respectively

3: for batch btCT of X do

4: for incoming input x of btCT do

5: Compute distance ϕi between x and all prototypes vi,

i = 1 · · · |V | = I, as follows:

If (inaction(vi) > 0) ϕi = inaction(vi) · dist(vi, x)

Else ϕi = dist(vi, x) end if (1)

Such that inaction(vi) = 1 − α (CT −vi.LT U)

6: Compute list of nearest prototypes S based on sorted index I such that

S = createSortedList(I, (x, y)) : (ϕx ≤ ϕy)

7: check = uncertainty(x) and within budget();

8: if check = true then

9: Query the label of x

10: else

11: x.label = unknown

12: end if

13: if S 6= {} then

14: Let j be the index of the closest prototype: j = S(1)

15: if x.label = unknown then

16: Assign the data item to vj

17: else

18: if x.label = vj .label then

19: Reinforce vj with x using only the common features:
vj = vj + α CT −LT U (x − vj)
20: Add the non-common features of x to vj : vj .
feature = α CT −LT U (x.feature)
21: else
22: Go to line 26
23: end if
24: end if
25: else
26: Initialize a new prototype:
vnew=x
27: vnew.label = x.label;
vnew. LT U = CT
28: V = V ∪ {vnew}
29: end if
30: end for
31: Update winning clusters in btCT with LT U = CT
32:
CT = CT + 1;
33: end for

Advantages: The knowledge should be gained by asking an expert for feedback. The algorithm should be highly self-dependent, by asking the expert only labels for a limited number of items. Therefore, we propose an original approach that combines different aspects - such as online learning and active learning - to build a hybrid classifier, AOMPC. AOMPC learns from both, labeled and unlabeled data, in a continuous and evolving way. In this context, AOMPC is designed to distinguish between relevant and irrelevant SM data related to a crisis situation in order to identify the needs of individuals affected by the crisis.

IV. ACTIVE ONLINE MULTIPLE PROTOTYPE CLASSIFIER (AOMPC)

A. Active Learning

AOMPC is an algorithm that employs active learning, making it highly adaptable in identifying relevant data within social media streams during crisis situations. It actively involves a user, typically a human expert, to enhance its performance. When AOMPC encounters data items it finds uncertain or ambiguous about their relevance to a specific crisis event, it solicits input from the user, asking them to label these items as either relevant (containing pertinent information about the crisis) or irrelevant (lacking relevance to the event). Once the user provides labels, AOMPC proceeds to classify the items accordingly and assigns them to clusters. These clusters represent groups of data items, with some clusters containing relevant information about the crisis, while others contain irrelevant data. AOMPC not only classifies actively labeled items but also employs unlabeled data items, utilizing the user's feedback to assign them to existing clusters or create new ones. This dynamic clustering approach enables AOMPC to continuously adapt and enhance its ability to extract crucial information from the social media data stream during a crisis.

B. AOMPC

In the context of active learning, the AOMPC algorithm initiates its process by evaluating the new input item. It assesses whether this item falls within the uncertainty region, which is the area where the algorithm is uncertain about the item's classification—whether it's relevant or irrelevant to the specific crisis event. Additionally, AOMPC checks whether there is an adequate budget available for labeling this item.
The presence of a budget constraint implies that there's a limited number of items the user can actively label. If both conditions are met—meaning the item is in the uncertainty region, and there is a remaining budget—then the algorithm proceeds with user intervention to label the item, enhancing its understanding of the data. The details regarding this process and its implications are typically elaborated on in subsequent sections of the algorithm's documentation or research paper.

C. Budget

Active learning in the context of online multiple prototype classification involves soliciting user feedback rather than automatically labeling incoming data items. To manage and restrict the frequency of user interventions, the concept of a "budget" is introduced. The budget can be thought of as the predefined limit on the number of queries made to the user. This approach is designed to strike a balance between harnessing user input for improving classification and minimizing user involvement, ensuring that the number of user queries remains within the budget constraints. The method used for implementing active learning in this context is adapted from a specific approach presented in related literature, which serves as a foundation for integrating active learning into online multiple prototype classification.

D. **Data Items to Query**

In active learning, the process of querying labels involves a preliminary step of selecting which specific data points to query. This selection is critical in optimizing the learning process. The primary criterion for choosing data points is identifying those for which the classifier demonstrates a lack of confidence in making assignment decisions. In other words, the focus is on selecting data points that the classifier finds uncertain or ambiguous in terms of their classification. This approach maximizes the value of user feedback in improving the classifier's performance by concentrating on the most informative and challenging data points.

E. **Feasibility Study**

Preliminary investigation examine project feasibility, the likelihood the system will be useful to the organization. The main objective of the feasibility study is to test the Technical, Operational and Economical feasibility for adding new modules and debugging old running system. All system is feasible if they are unlimited resources and infinite time. There are aspects in the feasibility study portion of the preliminary investigation:

1) Economic Feasibility: A system can be developed technically and that will be used if installed must still be a good investment for the organization. In the economical feasibility, the development cost in creating the system is evaluated against the ultimate benefit derived from the new systems. Financial benefits must equal or exceed the costs.
The system is economically feasible. It does not require any addition hardware or software. Since the interface for this system is developed using the existing resources and technologies available at NIC, There is nominal expenditure and economical feasibility for certain.

2) Operational Feasibility: Proposed projects are beneficial only if they can be turned out into information system. That will meet the organization‘s operating requirements. Operational feasibility aspects of the project are to be taken as an important part of the project implementation. Some of the important issues raised are to test the operational feasibility of a project includes the following the management issues and user requirements have been taken into consideration. So there is no question of resistance from the users that can undermine the possible application benefits. The well-planned design would ensure the optimal utilization of the computer resources and would help in the improvement of performance status.

3) Technical Feasibility: The technical issue usually raised during the feasibility stage of the investigation includes the following:

Does the necessary technology exist to do what is suggested? Do the proposed equipments have the technical capacity to hold the data required to use the new system?

•Will the proposed system provide adequate response to inquiries, regardless of the number or location of users?

•Can the system be upgraded if developed create, establish and maintain a workflow among various entities in order to facilitate all concerned users in their various capacities or roles. Permission to the users would be granted based on the roles specified. Therefore, it provides the technical guarantee of accuracy, reliability and security. The software and hard requirements for the development of this project are not many and are already available in- house at NIC or are available as free as open source.

•Are there technical guarantees of accuracy, reliability, ease of access and data security?

Earlier no system existed to cater to the needs of Secure Infrastructure Implementation System‘. The current system developed is technically feasible. It is a web based user interface for audit workflow at NIC-CSD. Thus it provides an easy access to the users.

E. **Software Requirements**

Operating System: Windows 7 User Interface: HTML, CSS Client-side Scripting: JavaScript Programming Language : Java
Web Applications: JDBC, Servlets, JSP
IDE/Workbench: My Eclipse 8.6
Database: Oracle 11g
Server Deployment: Tomcat 7.0

F. **Hardware Requirements**

Processor : Intel core i3 or above
Hard Disk : 500GB or more

V. RESULT ANALYSIS

The basic principle behind this method is that the longer a prototype has been stale (that is, it has not been changed), the slower it should migrate to a new location. The learning rate is a function of the prototype's previous success (i.e., may be viewed as a forgetting factor). The learning rate is used to determine the winning prototype. The label is queried if there is an uncertainty identified (see Section 3.2) and adequate money is available. Otherwise (for example, due to a lack of funds), the winning prototype determines the label. When a prototype outperforms all other prototypes in its vicinity based on the requested label, it is modified to travel in the direction of the new arriving item (figures 1-2). If the new input has additional textual characteristics, the prototype's feature vector is expanded to include them. AOMPC is capable of accommodating additional features in general. The evolution of the vocabulary through time is recorded in the case of textual input, as in this study. When no existing prototypes are close enough to the new item (figure 3), a new prototype is built to accommodate it (figure 4-6). The distance between the input and the existing prototypes is computed in Algorithm 1. (e.g., Euclidean distance in Algorithm 1). We utilise the Jaccard coefficient as a text-based distance (dist text) because most SM items include a textual description (e.g., tweets). We use a combined distance measure (dist text+dist geo)/2 if the social media items include two parts: the message content and the geo-location, which specifies where the message was sent in terms of coordinates. In Algorithm 1, steps 4-7, dist text refers to the Jaccard coefficient, whereas dist geo refers to the Haversine distance [15], [5]. Latitude and longitude are used to express the coordinates. Furthermore, Algorithm 1 steps 4-12 are linked to the active learning section. The algorithm begins by determining if the new input item falls within the range of uncertainty between the relevant and irrelevant prototypes and whether there is enough budget for labelling this item.

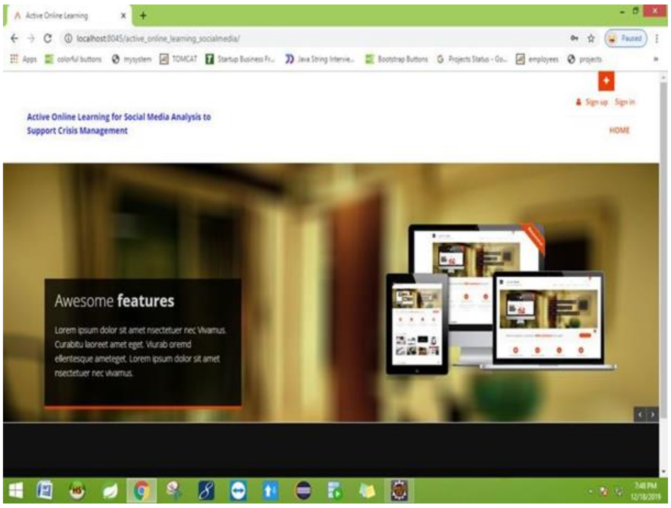

Figure 1 : Opening web page of the Active Online Learning for Social Media Analysis to Support Crisis Management Website.

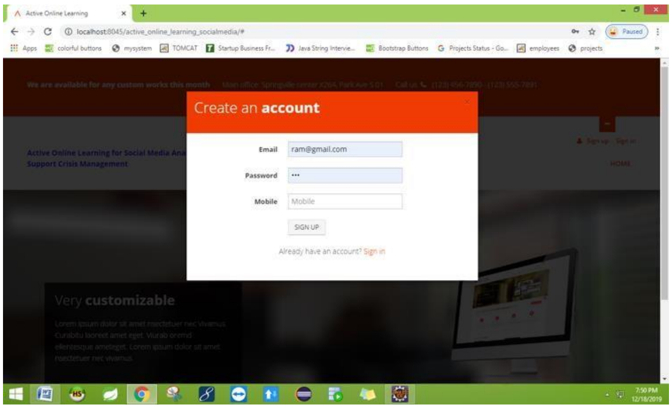

Figure 2: Admin sign up page.

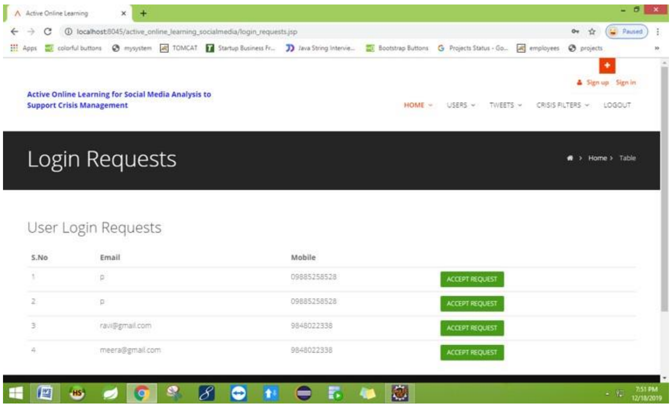

Figure 3: Admin home page where admin can accept the requests of the user.

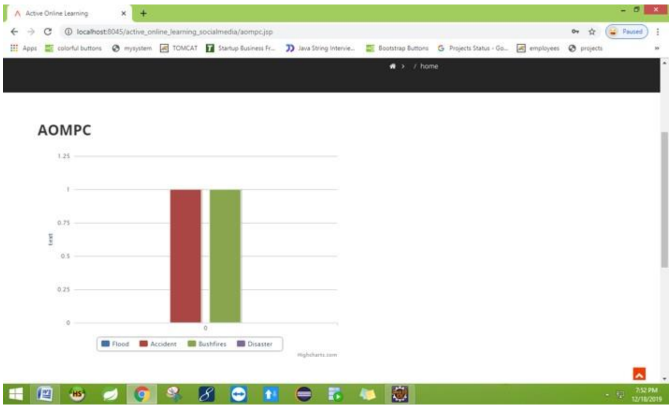

Figure 4: Bar graph of the crisis.

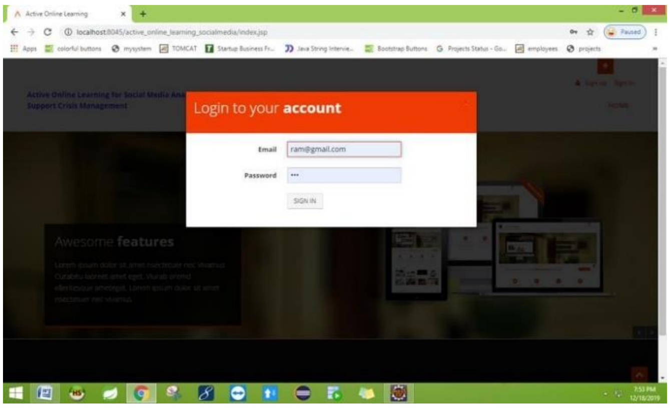

Figure 5: Login through the user credentials.

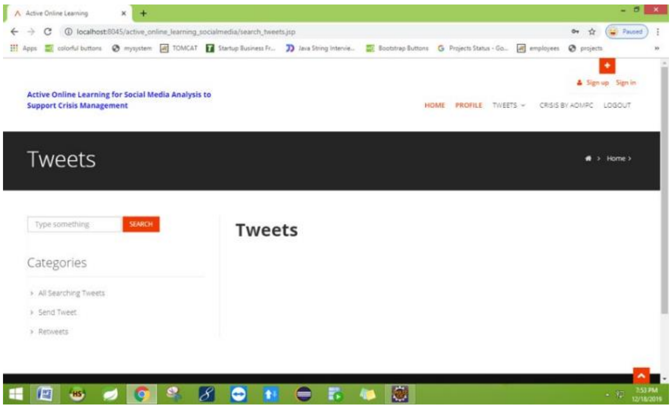

Figure 6: User searching tweets.

VI. CONCLUSION

The presented framework offers a streaming analysis approach designed to differentiate between relevant and irrelevant data items. It effectively incorporates the user into the learning process through the utilization of an active learning mechanism. To validate the framework's performance and adaptability, it was rigorously evaluated using various datasets, each with distinct parameters and active learning strategies. The assessment encompassed synthetic datasets, which were used to gain insights into the algorithm's behavior, as well as real-world social media datasets related to crisis situations. To showcase the effectiveness of the proposed algorithm, AOMPC, it was compared against a range of existing algorithms, illustrating its superior performance across diverse parameter settings.

Moreover, the framework has the potential for extension to address various challenges. For instance, it can be enhanced by incorporating a dynamic budget, allowing for more flexible resource allocation. Additionally, the ability to dynamically remove obsolete clusters can be integrated, improving the algorithm's adaptability to evolving data streams. Furthermore, generalization techniques can be implemented to handle non-contiguous class distribution, increasing the algorithm's versatility and applicability to a wider range of scenarios.

In summary, the presented framework introduces a streaming analysis approach with active learning to distinguish between relevant and irrelevant data items. Its thorough evaluation and the potential for future enhancements make it a valuable tool for processing data streams, particularly in the context of crisis management and social media analysis.

VII. REFERENCES

[1]. Mayuri, S., Waghmare., Tarun, Yengantiwar. (2020). Analysis of Active Learning for Social Media to Support Crisis Management. International journal of scientific research in science, engineering and technology, 7(4):291-294. doi: 10.32628/IJSRSET207476

[2]. Daniela, Pohl., Abdelhamid, Bouchachia., Hermann, Hellwagner. (2020). Active Online Learning for Social Media Analysis to Support Crisis Management. IEEE Transactions on Knowledge and Data Engineering, 32(8):1445-1458. doi: 10.1109/TKDE.2019.2906173

[3]. Claudio, Sapateiro., Pedro, Antunes., Gustavo, Zurita., Nelson, Baloian., Rodrigo, Vogt. (2009). Supporting Unstructured Activities in Crisis Management: A Collaboration Model and Prototype to Improve Situation Awareness. 101-111.

[4]. P. Krishna Kishore, S. Ramamoorthy, V.N. Rajavarman, ARTP: Anomaly based real time prevention of Distributed Denial of Service attacks on the web using machine learning approach, International Journal of Intelligent Networks, Volume 4, 2023, Pages 38-45, ISSN 2666-6030, https://doi.org/10.1016/j.ijin.2022.12.001.

[5]. Patrycja, Krawczuk., Shubham, Nagarkar., Ewa, Deelman. (2021). CrisisFlow: Multimodal Representation Learning Workflow for Crisis Computing. doi: 10.1109/ESCIENCE51609.2021.00052

[6]. Mayuri, S., Waghmare., Tarun, Yengantiwar. (2020). Analysis of Active Learning for Social Media to Support Crisis Management. International journal of scientific research in science, engineering and technology, 7(4):291-294. doi: 10.32628/IJSRSET207476

[7]. Daniela, Pohl., Abdelhamid, Bouchachia., Hermann, Hellwagner. (2018). Batch-based active learning: Application to social media data for crisis management. Expert Systems With Applications, 93:232-244. doi: 10.1016/J.ESWA.2017.10.026

[8]. Ming-Fu, Hsu., Ping-Feng, Pai. (2013). Incorporating support vector machines with multiple criteria decision making for financial crisis analysis. Quality & Quantity, doi: 10.1007/S11135-012-9735-Y

[9]. Abderrazak, Boumahdi., Mahmoud, El, Hamlaoui., Mahmoud, Nassar. (2020). Crisis Management Systems: Big Data and Machine Learning Approach.. doi: 10.5220/0009790406030610

[10]. Lida, Huang., Gang, Liu., Tao, Chen., Hongyong, Yuan., Panpan, Shi., Miao, Yujia. (2021). Similarity-based emergency event detection in social media. doi: 10.1016/J.JNLSSR.2020.11.003

[11]. Krishna Kishore, P., Prathima, K., Eswari, D.S., Goud, K.S. (2023). Bidirectional LSTM-Based Sentiment Analysis of Context-Sensitive Lexicon for Imbalanced Text. In: Bhateja, V., Sunitha, K.V.N., Chen, YW., Zhang, YD. (eds) Intelligent System Design. Lecture Notes in Networks and Systems, vol 494. Springer, Singapore. https://doi.org/10.1007/978-981-19-4863-3_27

[12]. Julien, Bohné., Yiming, Ying., Stéphane, Gentric., Massimiliano, Pontil., Massimiliano, Pontil. (2018). Learning local metrics from pairwise similarity data. Pattern Recognition, doi: 10.1016/J.PATCOG.2017.04.002

[13]. Xingfa, Qiu., Qiaosha, Zou., C., J., Richard, Shi. (2021). Single-Pass On-Line Event Detection in Twitter Streams. doi: 10.1145/3457682.3457762

[14]. Kilaru, S., Lakshmanachari, S., Kishore, P.K., Surendra, B., Vishnuvardhan, T. (2017). An Efficient Probability of Detection Model for Wireless Sensor Networks. In: Satapathy, S., Prasad, V., Rani, B., Udgata, S., Raju, K. (eds) Proceedings of the First International Conference on Computational Intelligence and Informatics . Advances in Intelligent Systems and Computing, vol 507. Springer, Singapore. https://doi.org/10.1007/978-981-10-2471-9_56

[15]. Liu, Yaopeng., Hao, Peng., Jianxin, Li., Yangqiu, Song., Xiong, Li. (2020). Event detection and evolution in multi-lingual social streams. Frontiers of Computer Science, doi: 10.1007/S11704-019-8201-6

[16]. Minale, Ashagrie, Abebe., Joe, Tekli., Fekade, Getahun., Richard, Chbeir., Gilbert, Tekli. (2020). Generic metadata representation framework for social-based event detection, description, and linkage. Knowledge Based Systems, doi: 10.1016/J.KNOSYS.2019.06.025

[17]. Munivara Prasad, K., Samba Siva, V., Krishna Kishore, P., Sreenivasulu, M. (2019). DITFEC: Drift Identification in Traffic-Flow Streams for DDoS Attack Defense Through Ensemble Classifier. In: Peng, SL., Dey, N., Bundele, M. (eds) Computing and Network Sustainability. Lecture Notes in Networks and Systems, vol 75. Springer, Singapore. https://doi.org/10.1007/978-981-13-7150-9_32

[18]. Xi, Chen., Xiangmin, Zhou., Timos, Sellis., Xue, Li. (2018). Social event detection with retweeting behavior correlation. Expert Systems With Applications, doi: 10.1016/J.ESWA.2018.08.022

[19]. Jonathon, S., Hare., Sina, Samangooei., Mahesan, Niranjan., Nicholas, Gibbins. (2015). Detection of Social Events in Streams of Social Multimedia. International Journal of Multimedia Information Retrieval, doi: 10.1007/S13735-015-0085-0

[20]. Momna, Anam., Basit, Shafiq., Shafay, Shamail., Soon, Ae, Chun., Nabil, R., Adam. (2019). Discovering Events from Social Media for Emergency Planning. doi: 10.1145/3325112.3325213

[21]. Wanlun, Ma., Zhuo, Liu., Xiangyu, Hu. (2019). Online Event Detection in Social Media with Bursty Event Recognition. doi: 10.1007/978-981-15-0758-8_14

Cite this article as :

Vankipuram Lavanya, Dr. D. Shobha Rani, "Active online Multiple Prototype Classifier to Support Crisis Management", International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Online ISSN : 2394-4099, Print ISSN : 2395-1990, Volume 10 Issue 6, pp. 267-277, November-December 2023. Available at doi : https://doi.org/10.32628/IJSRSET2310611
Journal URL : https://ijsrset.com/IJSRSET2310611