ISSN 2319-5991 www.ijerst.com
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Peer Reviewed, Referred & Indexed Journal

Research Paper

ACTIVE ONLINE LEARNING FOR SOCIAL MEDIA ANALYSIS TO SUPPORT CRISIS MANAGEMENT

[1]Dr. S. SANJEEVA RAO, [2]S. NAVYASRI, [3]TANUSRI JADHAV, [4]S.SAI VAMSHI, [5]CH. SURESH

[1]Assistant Professor,[2345]Students, Department of Computer Science and Design, Teegala Krishna Reddy Engineering College, Medbowli, Meerpet, Balapur, Hyderabad-500097

ABSTRACT

The rapid growth of social media platforms has transformed them into critical sources of real-time information during emergencies and crisis situations. Millions of users actively share updates, images, and opinions, which can provide valuable insights for authorities if analyzed effectively. However, the massive volume, unstructured nature, and presence of irrelevant or misleading content make it challenging to extract meaningful crisis-related information. Traditional systems relying on manual monitoring or static models fail to handle real-time data streams efficiently. To address these challenges, this project proposes an intelligent system based on Active Online Multiple Prototype Classification (AOMPC) for real-time crisis detection and analysis. The system continuously processes streaming social media data, classifies posts into relevant crisis categories, and adapts dynamically through online learning. It incorporates active learning strategies that request labeling only for uncertain data, thereby reducing manual annotation effort while improving accuracy. The proposed system integrates Natural Language Processing (NLP), machine learning, and role-based access mechanisms to provide a scalable and secure platform. Administrators can monitor suspicious users, while investigators can analyze event-specific data for informed decision-making. The system is implemented using Python, Django, and MySQL, ensuring flexibility and scalability. By enabling real-time crisis identification and filtering of relevant information, the proposed solution enhances situational awareness, reduces response time, and supports efficient crisis management operations.

Keywords: Social Media Analysis, Crisis Management, Active Learning, Online Learning, AOMPC, Machine Learning, NLP

I. INTRODUCTION

Social media has emerged as a powerful tool for communication and information sharing, especially during crisis situations such as natural disasters, accidents, and emergencies [1]. Platforms like Twitter and Facebook provide real-time updates from users who act as eyewitnesses [2]. These platforms generate large volumes of data that can be valuable for crisis response if analyzed properly [3]. However, the unstructured and noisy nature of social media data makes it difficult to extract meaningful insights [4]. Traditional crisis management systems rely heavily on manual data analysis, which is inefficient and time-consuming [5]. Automated systems using machine learning have been introduced to overcome these challenges [6]. Early approaches focused on keyword-based filtering, but they often misclassify irrelevant posts [7]. More advanced systems use Natural Language Processing techniques to analyze textual data [8]. Researchers have explored clustering and classification methods to identify crisis-related information [9]. Offline clustering methods help analyze events after they occur [10]. However, they are not suitable for real-time crisis detection [11]. Online learning methods have been proposed to process streaming data dynamically [12]. These methods adapt to new information without retraining from scratch [13]. Active learning further improves efficiency by selecting only important data for labeling [14]. Combining active learning with online learning enhances classification accuracy [15].

The proposed system introduces an Active Online Multiple Prototype Classifier (AOMPC) to address the limitations of existing approaches [16]. This classifier processes data streams in real time and continuously updates its knowledge [17]. It uses multiple prototypes to represent different classes, improving robustness against noisy data [18]. The system also incorporates active learning strategies to reduce labeling costs [19]. When uncertain data is detected, the system queries users for feedback [20]. This approach improves classification performance while minimizing manual effort [21]. Social media platforms are increasingly used by emergency responders for information gathering [22]. Integrating machine learning with crisis management systems enhances decision-making capabilities [23]. The proposed system provides role-based access for users, administrators, and investigators [24]. It enables monitoring of suspicious activities and identification of crisis-related posts [25]. The system also supports real-time alerts and visualization of crisis events [26]. Technologies such as Python, Django, and MySQL are used for implementation [27]. The architecture ensures scalability and efficient data processing [28]. By leveraging social media data effectively, the system improves situational awareness [29]. Overall, the proposed approach provides a reliable and efficient solution for crisis detection and management [30].

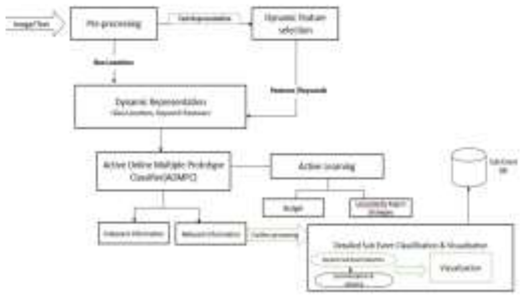
II. LITERATURE SURVEY

Recent research in crisis management has focused on leveraging social media data for real-time analysis and decision-making [1]. Deep learning models such as BERT and RoBERTa have been widely used for detecting crisis-related content [2]. These models capture contextual information and improve classification accuracy [3]. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are also used for text classification tasks [4]. Active learning techniques have gained attention for reducing labeling effort [5]. Methods such as uncertainty sampling and margin sampling help identify informative data points [6]. These approaches improve model performance with minimal labeled data [7]. Machine learning pipelines integrating NLP techniques are used for crisis detection and verification [8]. These pipelines help identify fake or misleading information [9]. Online learning algorithms are effective for processing streaming data [10]. Incremental learning models adapt to new data without retraining [11]. Semi-supervised learning techniques combine labeled and unlabeled data for improved accuracy [12]. Multiple prototype classifiers provide better representation of complex data distributions [13]. Geolocation techniques are used to map crisis events spatially [14]. These methods help identify affected regions in real time [15].

Further studies emphasize the importance of integrating multiple techniques for effective crisis management [16]. Hybrid models combining machine learning and rule-based approaches improve performance [17]. Sentiment analysis is used to understand public emotions during crises [18]. Topic modeling techniques identify emerging trends and events [19]. Social media analytics frameworks provide real-time monitoring capabilities [20]. Visualization tools help present data in an understandable format [21]. Active learning systems incorporate human feedback for continuous improvement [22]. Budget-based strategies limit the number of queries for labeling [23]. Online feature selection techniques improve efficiency in streaming environments [24]. Data preprocessing methods such as noise removal and normalization enhance data quality [25]. Big data technologies like Apache Kafka and Spark enable real-time processing [26]. Cloud platforms provide scalability and storage capabilities [27]. Ethical considerations such as data privacy and bias reduction are also important [28]. Research highlights the need for reliable and scalable systems [29]. Overall, existing studies demonstrate the effectiveness of combining machine learning, NLP, and active learning for crisis management [30].

III. PROPOSED SYSTEM

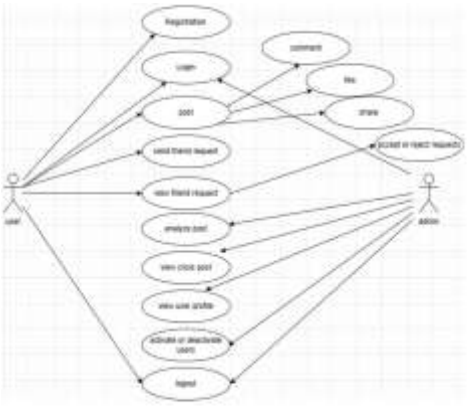
The proposed system introduces an advanced framework for real-time crisis detection using social media data. It is built on the Active Online Multiple Prototype Classifier (AOMPC), which enables continuous learning from streaming data. Unlike traditional models, the system does not require complete retraining when new data arrives. Instead, it updates its knowledge dynamically, making it suitable for real-time applications. The system processes user-generated content, analyzes textual information using NLP techniques, and classifies posts into different crisis categories such as accidents, floods, and fires. It also detects misleading or harmful content and flags it for further investigation.

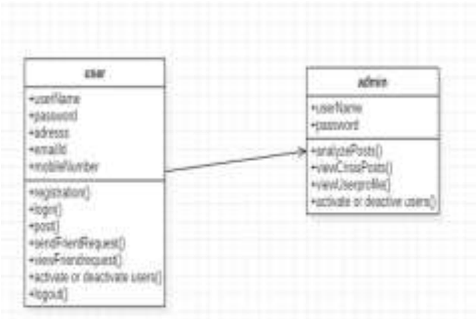


The system integrates active learning to improve efficiency and reduce manual effort. When uncertain data is encountered, the system requests labeling from users or administrators. This selective labeling approach ensures that only important data is annotated, reducing workload while improving accuracy. The system also provides role-based access, allowing administrators to monitor users and investigators to access detailed reports. The backend is implemented using Python and Django, while MySQL is used for data storage. The system is scalable, secure, and capable of handling large volumes of real-time data, making it highly effective for crisis management applications.

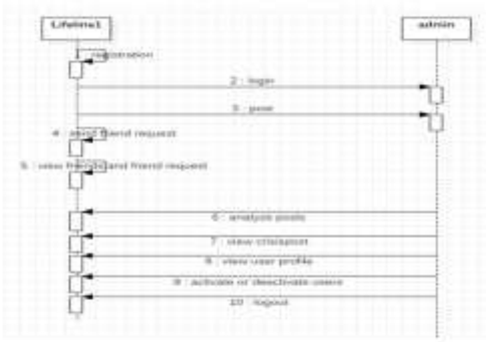
IV. SYSTEM DESIGN

The system design is based on a modular architecture that integrates data collection, processing, classification, and visualization components. The data flow begins with the collection of social media posts, which are then preprocessed to remove noise and extract relevant features. The processed data is passed to the AOMPC classifier, which categorizes posts into different crisis events. The system also includes an active learning module that identifies uncertain data and requests user input for labeling. This improves the accuracy and adaptability of the model over time.

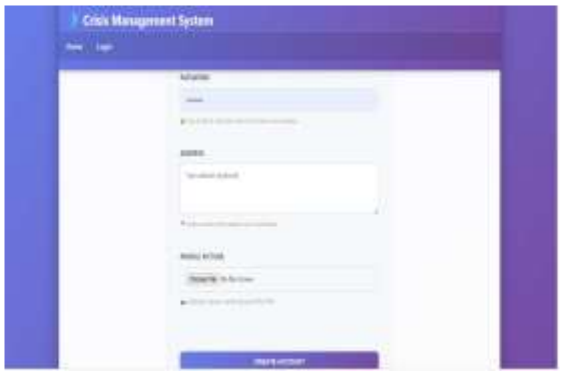


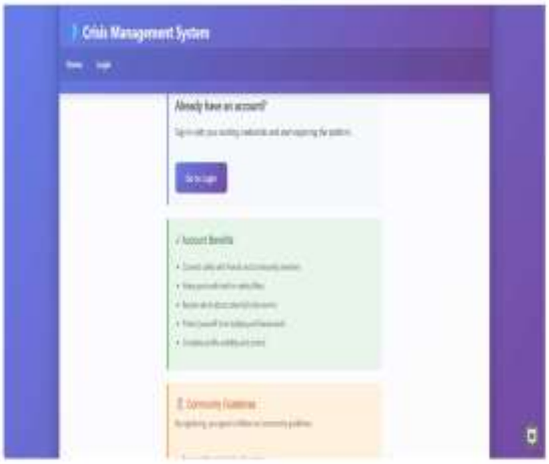


The architecture includes three main user roles: users, administrators, and investigators. Users can create and share posts, while administrators monitor activities and manage the system. Investigators can access detailed reports and analyze crisis events. The system also includes visualization tools that display trends, event distributions, and real-time alerts. UML diagrams such as use case, class, sequence, and activity diagrams are used to represent system functionality and interactions. The design ensures scalability, reliability, and security, making it suitable for real-world crisis management applications.



V. RESULTS





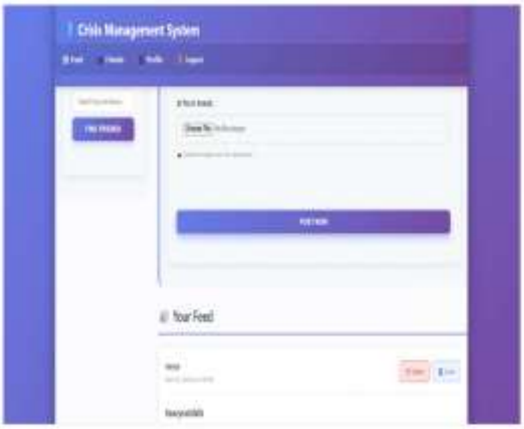
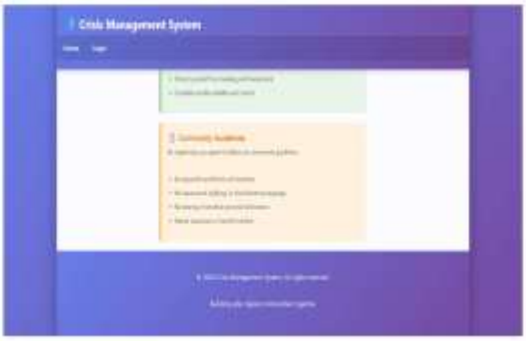


Fig 8.8: Post files



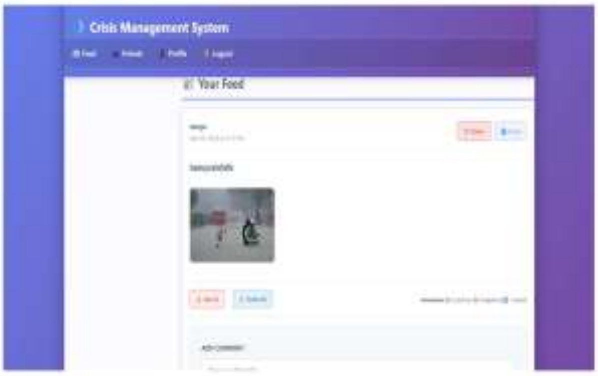
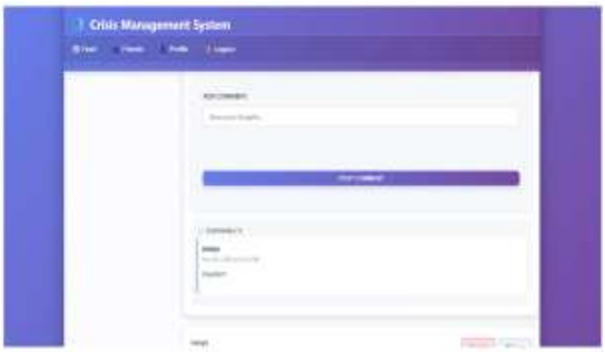
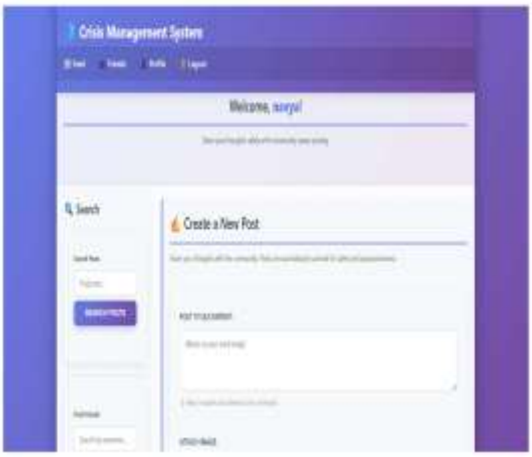
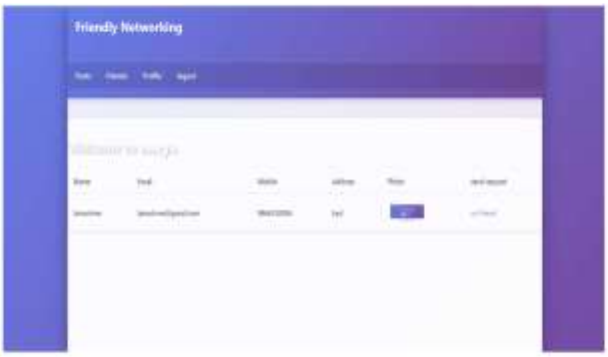


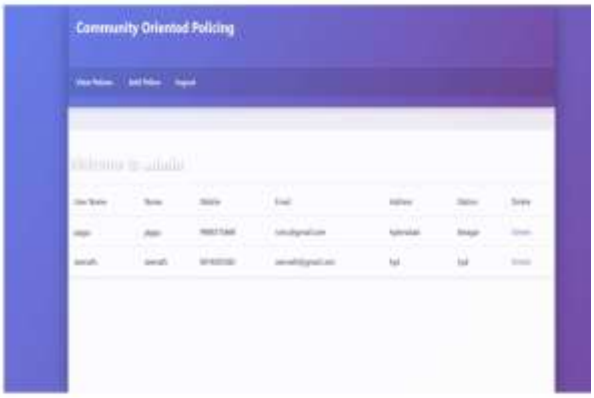
Fig 8.9: Feed Page

Fig 8.6: Login page









VI. CONCLUSION

The proposed system demonstrates an effective approach to leveraging social media data for real-time crisis management. By integrating active learning with online learning techniques, the system addresses the limitations of traditional methods that rely on static models and manual analysis. The use of the AOMPC classifier enables continuous adaptation to new data, ensuring accurate classification of crisis-related posts. The system also incorporates NLP techniques to analyze textual data and identify relevant information. Role-based access control enhances security and ensures that sensitive data is accessible only to authorized users. The integration of visualization tools and real-time alerts improves situational awareness and supports timely decision-making. Additionally, the system reduces manual effort through selective labeling, making it efficient and scalable. Overall, the proposed solution provides a reliable and intelligent framework for crisis detection and management. It has the potential to significantly improve emergency response systems by enabling faster and more accurate identification of critical events.

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