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# Disaster Classification and Assessment

*Namratha Jay, **Kavyasri M N, ***Monisha S, ****Nihari H.R, *****Milind K.G

**(Department of Computer Science, Malnad College Of Engineering, Hassan, India*
***(Department of Computer Science, Malnad College Of Engineering, Hassan, India*
****(Department of Computer Science, Malnad College Of Engineering, Hassan, India*
*****(Department of Computer Science, Malnad College Of Engineering, Hassan, India*
******(Department of Computer Science, Malnad College Of Engineering, Hassan, India*

**ABSTRACT**

Natural disasters such as floods, earthquakes, and wildfires pose significant challenges to disaster response and management. These events require rapid identification and effective response strategies to minimize losses and ensure timely recovery. Existing methods like satellite imaging and remote sensing are often limited due to high costs, noise interference, and limited perspectives. This report introduces a cutting-edge system leveraging Convolutional Neural Networks (CNNs) to detect and classify natural disasters from social media imagery. Utilizing a dataset of categorized disaster images, the system facilitates rapid decision-making, reduces response time, and enhances disaster preparedness. This work provides a comprehensive analysis of system design, implementation, and testing, underscoring its potential for transforming disaster management practices.

***Keywords -*** CNN, Machine learning, Disaster

## I. INTRODUCTION

Disasters, whether natural or human-induced, have profound impacts on communities and infrastructure. Earthquakes, floods, and other catastrophes require immediate and effective response strategies to mitigate damage and facilitate recovery. However, current methods of disaster detection often involve manual data processing, expert evaluation, and satellite imagery, which can be costly, time-consuming, and limited by environmental noise. Additionally, social media, despite being a rich source of real-time disaster data, remains underutilized due to challenges like noisy image streams and the need for advanced classification techniques. This report explores the development of a Convolutional Neural Network (CNN)-based model for disaster detection, addressing the limitations of traditional methods. By leveraging social media images and a novel disaster dataset comprising four classes—drought, urban fire, water disaster, and non-damage—the proposed system offers a rapid, automated solution for disaster classification. The primary objectives include improving accuracy, reducing response time, and enhancing disaster management efficiency. Through detailed analysis, design, and testing, this work demonstrates how advanced machine learning techniques can revolutionize disaster response systems, ensuring better preparedness and mitigation strategies.

## II. PROBLEM STATEMENT

The increasing frequency and intensity of natural and man-made disasters result in significant loss of life, damage to infrastructure, and disruption of communities.

Current disaster management systems face challenges in utilizing diverse data sources, such as social media, satellite imagery for timely and effective analysis.

This project aims to develop a disaster management framework that integrates machine learning models and Geographic Information Systems (GIS) to enhance disaster detection, classification, and risk-based response planning.

## III. LITERATURE SURVEY

### A. Crowdsourcing Incident Information for Disaster Response Using Twitter

Social media platforms, particularly Twitter, have emerged as valuable resources for real-time information dissemination. Studies have demonstrated the utility of Twitter data in understanding human behavior, societal dynamics, and natural disaster management. For instance, Sakaki et al. (2010) used tweets to detect earthquakes and other critical events, showcasing Twitter as a "social sensor" for real-time event detection. Similarly, Imran et al. developed machine learning models to categorize disasterrelated tweets into actionable insights, such as alerts about casualties, infrastructure damage, and relief efforts. These models achieved high accuracy but emphasized the necessity of robust training datasets to ensure reliability.

Geo-tagged tweets have been employed in various studies to map human mobility and enhance incident reporting systems. Kurkcu et al. (2016) utilized Density-Based Spatial Clustering of Applications with Noise (DBSCAN) to study human mobility through Twitter data, highlighting the potential of social media for understanding travel patterns. Moreover, the study extended this concept to incident management, where geo-tagged tweets provided time-sensitive updates on traffic incidents, often outperforming traditional systems like 511NY in terms of timeliness.

Literature underscores the significance of leveraging social media, especially Twitter, as a supplementary data source for incident management. While it cannot replace traditional systems due to reliability concerns, its ability to provide real-time, geo-tagged, and diverse information makes it a powerful tool for enhancing disaster response and urban mobility analysis.

**B.An Integrated Convolutional Neural Network and Sorting Algorithm for Image Classification for Efficient Flood Disaster Management**

Drones are increasingly being used for disaster management due to their flexibility, cost-effectiveness, and efficiency. They can assist in activities such as pre-disaster mapping, real-time monitoring during disasters, and postdisaster damage assessments. Linardos et al. highlighted the integration of big data, such as crowdsourced information, web mapping, and social media, to enhance pre- and post-disaster management. Lin et al. utilized Baidu big data and a multi-layer perceptron neural network to improve the estimation of relief supply demands in urban flood scenarios. Anbarasan et al. proposed a binary machine learning approach for flood detection using attributes like rain sensor data and water levels, integrated with CNN models to enhance detection accuracy.

Convolutional Neural Networks (CNNs) are pivotal in image-based disaster management due to their ability to process grid-like data structures. Pereira et al. applied DenseNet and EfficientNet models to detect flood severity, achieving high accuracy on datasets like European Flood 2013 and MediaEval. Suha and Sanam highlighted the superior accuracy of pretrained CNN models over traditional models in assessing image-based disaster severity. Zhang et al. integrated CNNs with decision tree algorithms to enhance interpretability in flood management applications.

**C.A Machine Learning Approach to Formation of Earthquake Categories Using Hierarchies of Magnitude and Consequence to Guide Emergency Management"**

Machine learning (ML) techniques have been extensively applied to classify earthquake-related data to aid in disaster management. Naito et al. (2020) utilized convolutional neural networks (CNNs) and bag-of-visual-words models to classify building damages based on aerial photographs taken after the 2016 Kumamoto earthquake. Their model categorized damages into four levels, demonstrating the potential of CNNs in post-earthquake damage assessment. Similarly, Mangalathu et al. (2020) compared four ML algorithms—discriminant analysis, k-nearest neighbors (KNN), decision trees, and random forests (RF)—to classify building damage from the South Napa earthquake data. The RF algorithm emerged as the most accurate.

ML models have also been employed to estimate earthquake-induced losses, including fatalities and repair costs. Stojadinović et al. (2022) developed a framework combining RF with expert-defined repair cost matrices to predict building repair costs. While existing models excel in material damage classification, fewer studies focus on categorizing human casualties or integrating global datasets for generalizability. This gap is addressed in recent work by employing unsupervised learning techniques like k-means clustering to establish earthquake taxonomies.

These taxonomies classify earthquakes into low, medium, and high categories based on magnitude, fatalities, injuries, and monetary damages, offering a universal framework for resource allocation in disaster management.

**D.Flood prediction based on weather parameters using deep learning**

Various studies have utilized IoT and machine learning (ML) techniques, particularly Artificial Neural Networks (ANN), for flood prediction based on parameters such as water flow, water level, temperature, rainfall, and humidity. While ANN-based systems have demonstrated potential, they face limitations in real-time notifications and accuracy. Wireless Sensor Networks (WSNs) have been employed to monitor environmental conditions but similarly struggle with real-time responsiveness. Bayesian Forecasting Systems (BFS) address uncertainties by providing probabilistic flood forecasts, while classification techniques like Random Forest, Decision Tree, and Support Vector Machine (SVM) have also been applied to enhance flood management. Recent advancements include the use of hybrid models and neural network approaches, such as Quantum-behaved Particle Swarm Optimization, which have demonstrated high accuracy in evaporation prediction and flood management. Deep Neural Networks (DNNs), leveraging multiple hidden layers, have shown superior performance in flood prediction using seasonal data like temperature and rainfall intensity, outperforming traditional models like SVM, KNN, and Naïve Bayes in accuracy and error metrics. In parallel, the importance of imagery content for disaster response has been widely recognized. Early studies analyzed aerial and satellite images for rapid damage assessment, such as Turker and San's (2004) analysis of post-earthquake aerial images from the 1999 Izmit earthquake and Plank's (2014) review of Synthetic Aperture Radar (SAR) for damage assessment, which highlighted SAR's advantages over optical sensors. Additionally, Fernandez Galarreta et al. (2015) and Attari et al. (2017) emphasized the role of Unmanned Aerial Vehicles (UAVs) in capturing high-resolution oblique images for structural damage assessment, underscoring the value of combining aerial technologies with advanced analytics for disaster management.

### F.Rapid Damage Assessment Using Social Media Images by Combining Human and Machine Intelligence

The paper "Rapid Damage Assessment Using Social Media Images by Combining Human and Machine Intelligence" presents an automated image processing system for assessing disaster damage using social media images. The system collects tweets with disaster-related hashtags, filters duplicate and irrelevant images, and categorizes damage severity (severe, mild, or none) using a fine-tuned VGG16 deep learning model. A human-in-the-loop approach ensures experts validate and refine outputs, enhancing the model's performance. Tested during Hurricane Dorian (2019), the system analyzed 280,000 images over 13 days, filtering 26,000 damage-relevant images with a classification accuracy of 74%-76%. Its advantages include efficiency, scalability, cost-effectiveness, and the ability to process large-scale data in real-time, but it faces challenges like biases in social media coverage, false positives/negatives, data limitations, and dependence on human validation. The approach demonstrates the potential of combining automated systems and expert oversight to expedite damage assessment during disasters.

### E.Analysis of Social Media Data Using Multimodal Deep Learning for Disaster Response

The paper "Analysis of Social Media Data Using Multimodal Deep Learning for Disaster Response" presents a deep learning framework that integrates text and image data from social media to enhance disaster response analysis. Using the Crisis MMD dataset, the system focuses on two tasks: informativeness classification (determining whether a tweet is useful) and humanitarian classification (categorizing tweets into disaster-related themes like rescue or damage). It employs a CNN-based model for text processing and a fine-tuned VGG16 model for image classification, with high-level features from both modalities fused into a shared representation for final predictions. Multimodal training outperforms unimodal approaches, achieving F1-scores of 84.2 for informativeness and 78.3 for humanitarian tasks. While the approach demonstrates improved performance, scalability, and benchmarking for multimodal disaster analysis, it faces challenges such as limited dataset size, weak alignment between text and images, increased computational complexity, and the need for disaster-specific datasets for generalization. The research highlights the potential of multimodal architectures in capturing diverse signals for disaster management tasks.

## IV. RESULT TABLE

| Mode | Training Data (%) | Test Data (%) | Expected Accuracy | Obtained Accuracy |
|---|---|---|---|---|
| Crowdsourcing Incident Information for Disaster Response Using Twitter | Not specified | Not specified | Not explicitly stated | Not explicitly stated |
| Machine Learning for Earthquake Categories Using Magnitude and Consequences | 70% | 30% | Not explicitly stated | Approximately 83% |
| CNN and Sorting Algorithm for Image Classification in Flood Disaster Management | 70% | 15% | Not explicitly stated | 81% (DenseNet) and 83% (Inception v3) |
| Flood Prediction Using DNN | 80% | 20% | Not mentioned | 91.18% (DNN), 85.73% (KNN), |

| | | | | |
|---|---|---|---|---|
| | | | | 85.57% (SVM) |
| Multimodal Deep Learning for Disaster Response | 70% | 15% | Not mentioned | 84.4% (informativeness), 78.3% (humanitarian) |
| Rapid Damage Assessment Using Social Media Images | Not explicitly stated | Not explicitly stated | Not mentioned | 76% (damage detection), 74% (damage severity) |

| Criteria | [5] | Paper 2 | Paper 3 | Paper 4 |
|---|---|---|---|---|
| Research Objective | Integrates Twitter data with traditional systems for improved disaster response. | Classifies flood severity and prioritizes relief using CNNs and sorting algorithms. | Categorizes earthquakes into clusters for resource-efficient management. | Predicts floods using DNNs based on rainfall intensity and temperature data. |
| Methodology | Uses TF-IDF, NLP, and Naïve Bayes to classify tweets with 93% accuracy. | Combines Inception v3, DenseNet-121, and Merge Sort for image classification and ranking. | Uses k-means clustering on global earthquake data validated by ANOVA tests. | Trains DNN on historical data and compares with SVM, KNN, and Naïve Bayes. |
| Key Findings | Twitter provides broader coverage an insights missed by conventiona systems. | Efficiently allocates resources based flood severity a proximity | Develops a taxonomy linking magnitude, consequences, and resource needs. | DNN achieves the highest accuracy for early flood prediction. |
| Accura y | Achieves 93% accuracy in tweet classificatio . | Inception v3: 83%; DenseNet-121: 81%. | N/A (focuses on clustering, not classification). | DNN: 91.18%; Naïve Bayes: 87.01%; SVM: 85.57%; KNN: 85.73%. |
| Advan ges | Real-time updates, cost-effective, and complementary to traditional methods. | Low-cost, real-time monitoring with drones, and effective resource prioritization. | Globally applicable and prevents resource over- or under-allocation. | High accuracy and effective for resource-constrained regions. |
| Disadv tages | Prone to misinformat on, biases, and overrepreser tation of events. | Dataset constraints and limited visibility during disasters. | Limited real-time capabilities and requires manual updates. | Outdated dataset and limited parameter consideration. |

## V. CONCLUSION

The reviewed studies demonstrate the transformative potential of machine learning (ML) and technology in disaster management, offering innovative solutions for disaster response optimization. Techniques like crowdsourcing, clustering, CNNs, DNNs, and multimodal deep learning show promising results in real-time decision-making, resource allocation, early prediction, and damage assessment. Key advancements include improved accuracy rates, enhanced situational awareness, and efficient disaster relief through autonomous technologies like drones. However, challenges persist, such as limited datasets, outdated parameters, and noisy social media data. The need for more robust and diverse datasets, refined models, and comprehensive frameworks is emphasized. Future research should focus on integrating these approaches into a unified system for scalability and broader applicability. By addressing current limitations, ML-based systems can become more reliable, impactful, and widely adopted in disaster-prone regions.

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