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AI-based Disaster Classification using Cloud Computing

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Abstract: The combination of cloud computing and artificial intelligence (AI) offers a potent remedy for disaster management and response systems in this age of quickly advancing technology. Using text and image data gathered from social media sites, this project, makes use of the collective intelligence present in the data. We carefully trained a bidirectional LSTM model for textual analysis and a Convolutional Neural Network (CNN) model for image classification using Kaggle datasets. Our system's fundamental component is an API that is installed on an Amazon Web Services (AWS) EC2 instance. To improve performance and stability, the API is strengthened with load balancing, auto-scaling features, and multi-AZ redundancy. The API easily integrates with the trained models to determine whether the content is relevant to a disaster scenario when it receives input data. When a positive classification is made from the processed text or image, an alert mechanism sends out an email notification with important information about the disaster that was discovered. The abundance of user-generated content available on social media sites like Facebook, Instagram, and Twitter presents a special chance to improve the efficacy and efficiency of disaster relief operations. The main objective of this project is to use cutting-edge technologies to sort through massive amounts of social media data and derive useful insights in emergency situations.

Keywords: Machine Learning, Deep Learning, Artificial Intelligence, Cloud Computing, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Amazon Web Services (AWS), Elastic Compute Cloud (EC2)

1. INTRODUCTION

The volume of real-time information published during emergencies and disasters has become a priceless resource for disaster management and response in an era marked by the pervasive influence of social media. Text and imagery content from social media platforms provide a plethora of information that, when used wisely, can greatly improve the accuracy and timeliness of disaster response operations. However, the dynamic and unstructured nature of this data presents significant challenges for standard response approaches. By creating and implementing a state-of-the-art artificial intelligence (AI) and machine learning (ML) system for the real-time classification of social media content pertinent to disasters, our research seeks to close this gap. The backdrop of climate change and the rising frequency and severity of natural disasters highlight the growing significance of disaster management. The intensification of extreme and erratic weather patterns brought about by climate change has escalated natural disasters like hurricanes, wildfires, floods, and earthquakes. These disasters require more efficient and quick response systems because they pose serious risks to infrastructure, property, and human lives. To handle the demands of these increasingly urgent situations, traditional disaster management techniques—which sometimes rely on information that is manually processed and delayed—are no longer enough. Our study aims to provide a thorough knowledge of the catastrophic scenarios as they occur by utilizing multiple data modalities, including text and photos. Our goal is to improve the system's accuracy and adaptability in a variety of crisis scenarios by utilizing cutting-edge AI approaches. The system gains levels of complexity and capability from the integration of open APIs for image recognition and natural language processing, which makes it possible for it to effectively handle and interpret enormous volumes of unstructured data. This creative method to disaster management makes use of social media data's real-time nature to give emergency responders quick insights and useful information. Rapid information processing and classification capabilities of the system guarantee efficient resource allocation and response coordination. Our goal is to show how artificial intelligence (AI) and machine learning (ML) may be used to enhance catastrophe preparedness, response, and recovery in a time when the effects of climate change are posing greater challenges.

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2. CHALLENGES PRESENT IN THE EXISTING METHODS

Within the field of crisis management, current approaches face numerous obstacles that hinder their capacity to effectively and consistently use social media data for classification in real time. The large volume of unstructured social media content during crises is one of the main obstacles. The massive amount of data collected on multiple platforms, including text, photographs, makes it difficult to derive timely and useful insights. This flood of information frequently overwhelms current systems, which results in inefficient data processing and analysis. Furthermore, this difficulty is made worse by social media's dynamic and ever-evolving character, which allows for quick changes in the environment in response to breaking news and new narratives.

The integration of free APIs for content classification and identification is another major challenge. Although these APIs provide useful functionality, it is yet unclear how reliable and flexible they would be in different types of crisis situations. The performance of these APIs can be greatly impacted by variations in data quality, linguistic subtleties, and cultural contexts, which can result in inaccurate and inconsistent categorization results. Additionally, depending on third-party APIs increases the risk of service outages, changes to API specifications, and data privacy problems.

Another significant obstacle to the creation and application of AI and ML-based catastrophe classification systems is ethical considerations. Social media data collection, analysis, and distribution provide a number of difficult moral conundrums, such as those involving permission, privacy, and the possible spread of false information. Researchers and practitioners face a difficult balancing act when trying to strike a balance between the necessity of prompt disaster response and respect for individual privacy rights and ethical concerns. In addition, the inherent biases in social media data combined with the algorithms employed for categorization give rise to questions of accountability, transparency, and fairness in decision-making processes.

Deploying the system on a cloud infrastructure also presents a number of technical difficulties. In a cloud environment, scalability, dependability, and real-time responsiveness need to be guaranteed by meticulous architectural design, resource optimization, and ongoing oversight. The deployment process is further complicated by the need to manage expenses and reduce risks related to data security, compliance, and regulatory requirements. For successful resource allocation and workload adaptation, load balancing and auto-scaling methods must be integrated; nevertheless, establishing these components needs experience and careful design. In addition, the multidisciplinary character of disaster management demands cooperation and coordination between various stakeholders, such as emergency responders, legislators, scholars, and impacted communities. It might be difficult to bridge the gap between technical proficiency and domain knowledge because of misunderstandings, competing priorities, and opposing points of view. Achieving agreement among stakeholders with different backgrounds and interests on system specifications, performance measures, and ethical norms takes consistent engagement and communication.

3. RELATED WORKS

Analyzing disasters through social media data poses challenges due to noise and lack of structure. Extracting relevant information is difficult, leading to potential misclassification and overlooked data, causing false positives or negatives. Researchers seek innovative approaches, leveraging technologies like sensing, IoT, SM, big data analytics, and AI to enhance accuracy. Strategies include pre-alert systems based on congested regions, fuzzy-c, and GPS for predicting user locations. The study reviews current disaster management technologies, focusing on SM and AI, highlighting drawbacks like platform-centric SM analytics and reduced infrastructure costs. [1]

A study presents the real-time implementation of a Multi-Agent System (MAS) model for Disaster Management System (DMS). It outlines the architecture, deployment plan, and a web portal based on the recommended DMS. The paper details the system's components and the DMS's purpose, emphasizing the use of a web portal to create an automated workflow model and real-time cloud implementation. The proposed effort contributes to removing dynamic on-time dependency in favor of proactive dependent calculations. Research gaps suggest expanding the focus to include real-time operational, strategic, and decision-making management in DMS, along with thorough analysis and validation of the system life cycle stages. The potential use of a cloud-based augmented reality system is proposed for identifying damaged locations and optimizing transit routes. [2]

Limited research exists on picture change detection for anomaly identification. RaVÇ¸ n, an onboard satellite system, employs unsupervised machine learning to instantly detect extreme events like floods and landslides, minimizing data transport delays and conserving bandwidth. This approach highlights abnormalities without the need for pre-labeled data, enabling quicker reaction times and improved disaster preparedness. Despite challenges such as false positives and resource scarcity, RaVÆn signifies a promising development in space-based extreme event monitoring, offering immediate anomaly detection capabilities onboard [3]. To comprehend multilingual social media buzz during emergencies, the authors employ a robust model based on Multilingual BERT, enhanced with Manifold Mixup and a masking-based loss function. This results in accurate categorization of disaster-related tweets across various categories, including unseen disaster types. The approach enables real-time response and coordination across languages, utilizing social media data for immediate situation assessment. Zero-shot learning suggests potential expansion to additional languages without extra training data, strengthening cross-linguistic disaster preparedness. In essence, the study establishes a foundation for a more informed and coordinated approach to crisis resolution in a multilingual global community [4] and [5]. Addressing the challenge of timely disaster response due to a lack of annotated satellite imagery, the study proposes a creative solution utilizing knowledge transfer and semi-supervised learning. By fine-tuning a pre-trained model with a large set of unlabeled disaster photos and a small set of labeled ones, the approach achieves remarkable accuracy even with limited labels. This method enables effective disaster analysis in real-world scenarios, allowing clearer views from above for quicker response and more efficient relief efforts, spanning from identifying flood zones to monitoring wildfires. The research holds promise for enhancing disaster navigation and saving lives during tragedies [6] and [7]. Few articles effectively combine various methods to sift through tweets and accurately identify those related to disasters. The algorithm treats tweets as word sacks, rigorously analyzing them to extract relevant phrases like "flooded," "earthquake," or "fire," while disregarding hashtags and emoticons. Assigning weights to words based on community importance, the algorithm employs diverse classification algorithms to interpret and reach a consensus on the tweet's nature, distinguishing cries for assistance from casual musings. Despite challenges like keyword selection and adaptation to different disasters, this hybrid strategy significantly enhances the ability to locate disaster-related tweets amidst the Twitter noise. Emergency response teams can swiftly gather crucial data and direct aid effectively. Although there are still hurdles, this approach represents a substantial step in utilizing social media for positive impact, turning every tweet into a potential lifeline during emergencies [8].

Navigating through the overwhelming volume of disaster-related tweets to identify genuine pleas for assistance is akin to navigating a lightning-studded sky. However, AI training proves beneficial in this context. By assessing emotions expressed in tweets, beyond just words, the system discerns genuine distress amid the noise, focusing on those truly in need during a storm.[9] This approach transcends geographical boundaries, allowing assistance based on both location and digital distress levels. The research envisions AI as a guiding light amid the storm, aiding in managing information overload and connecting with those requiring help. Challenges like data gaps and ethical considerations, however, persist [10]. AI detectives, trained on extensive datasets of similar incidents, analyse high-resolution photos like detailed maps of destruction. Swiftly assessing scars from events like fires and floods, they pinpoint the centre and predict the spread. This enhanced vision allows for quicker response, resource optimization, and proactive preparation for future incidents. Despite challenges like missing data and ethical considerations, the potential is evident. Envision disaster response guided not just by location but also by the mapped damage on our planet, interpreted by AI and informed by Earth's cues. Technology assumes the role of a guardian angel in navigating disasters, using its knowledge of Earth's history to shape a resilient future. [11] Sentiment analysis on social media plays a vital role in disaster management, aiding in the identification of affected areas and optimizing relief efforts. This study contends that, particularly in disaster scenarios, the Bi-LSTM architecture surpasses CNN and GRU in accuracy for sentiment analysis. The superiority of Bi-LSTM is attributed to its effectiveness in extracting intricate contextual information from sequential data, particularly in spoken language. While acknowledging the utility of CNN and GRU in specific contexts, the prevailing research suggests that Bi-LSTM stands out as the most effective architecture for sentiment analysis in disaster management conditions [12]. One study introduces a disaster recovery and identification method leveraging smart devices and Twitter. Deep learning models and Natural Language Processing (NLP) are employed to categorize real-world disaster tweets based on factors like location and mood. The system comprises three modules: Sentiment Analysis, Disaster Recovery, and Disaster Identification. The Disaster Identification module utilizes a Bi-LSTM + Glove embedding deep learning model to identify disaster-related tweets. Simultaneously, the Sentiment Analysis module, employing a different deep learning model, assesses the sentiments of identified disaster tweets. The Disaster Recovery module schedules rescue teams based on areas with high negative emotions. The datasets include about 10,000 hand-classified disaster tweets and tweets expressing various emotions for sentiment analysis [13] and [14]. This project addresses Indonesia's wildfire challenge by developing an efficient predictive model for land and forest fire severity using images and machine learning. Three prefire vegetation parameters—vegetation greenness indices, vegetation wetness, and vegetation senescence—are utilized for forecasting postfire fire intensity. The study employs Sentinel-2 imagery and various linear regression and Artificial Neural Network (ANN) regression models. With an impressive accuracy exceeding 90 percentage, the research establishes that ANN regression, particularly using IRECI as the vegetation greenness parameter, is highly effective in predicting wildfire severity. The ANN model with IRECI demonstrates notable results, boasting an R2 value of 0.9154, indicating a significant correlation between observed and projected values. Additionally, its low Mean Absolute Percentage Error (MAPE) value of 9.52 percentage suggests minimal prediction error [15]. This kind of classification can also be used for data classification from crowdsensing. It is helpful in that domain for classifying the data as true or fake. This has been done using Machine Learning algorithms like Naïve Bayes, SVM, Decision Tree and Random Forest by Sahoo et al., in their work on Enhancing Data Integrity [16]. A wide range of approaches and conclusions are shown in the literature on catastrophe management with artificial intelligence and cloud computing. Cloud-based infrastructures and machine learning algorithms have been used in seminal research to increase the accuracy and speed of disaster response.

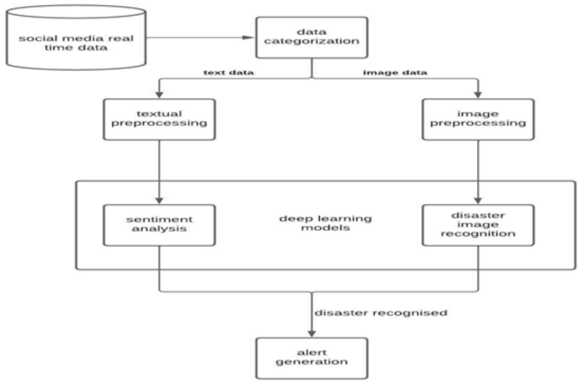

Figure 1. Proposed System Architecture

A new multimodal fusion paradigm was used in a later work [17] where they used cross modal and self attention for the improvement of learning from vast set of images, texts and their modalities. seventeen. Research has indicated that convolutional neural networks (CNNs) and natural language processing (NLP) are capable of efficiently handling vast amounts of unstructured data, as evidenced by their success in categorizing disaster-related information from social media. Although current approaches to catastrophe management and categorization have showed promise, they are not without flaws, including computational complexity and bias in the data. Certain strategies heavily depend on particular platforms, which might not fully utilize the range of data that is accessible. Furthermore, even while AI models can improve classification accuracy, they frequently call for a significant amount of computational power, which can be expensive and restrict scalability. Our method ensures more thorough coverage and effective processing of disaster data by combining cutting-edge AI models with scalable cloud computing solutions, thereby addressing these restrictions. Our approach seeks to enhance the precision and responsiveness of catastrophe management endeavours by emphasizing real-time data processing and integrating feedback loops.

4. PROPOSED SYSTEM

In the initial stage (Figure 1) data is retrieved through the API, and its type is identified. For textual data, preprocessing is applied to filter out noise, removing links, hashtags, and emojis. The cleaned text then undergoes analysis using a pre-trained Bi-LSTM model. If the data indicates a disaster, an email alert is generated. For image data, its size is augmented to match training set dimensions and processed through a CNN model. Classification includes Damaged Infrastructure, Fire Disaster, Human Damage, Land Disaster, and Non-Damage. If it identifies a disaster type (excluding non-damage), an email alert is triggered with the image attached. The entire architecture is deployed on an AWS EC2 server with a load balancer to facilitate auto-scaling of the application.

The process for classifying disasters using AI and ML is organized into multiple phases, starting with data gathering and ending with real-time implementation. Every stage is intended to tackle obstacles and advance the overall objective of creating a catastrophe management system that is both morally and practically sound.

A. Data Collection and Preprocessing Module

The method makes use of Kaggle datasets, which comprise real-time social media data about several disaster situations that include both text and photos. These datasets offer a wealth of data that can be used to train and test the models, guaranteeing that a variety of crisis scenarios are covered. Tokenization, which divides text into discrete words or tokens, is the first step in text preparation. Normalization then transforms text into a standard format, like lowercasing. After then, noise removal is done to get rid of unnecessary information like hashtags, mentions, and URLs. Lastly, to improve model comprehension, words are reduced to their base or root form through stemming or lemmatization.

A uniform size is applied to image data to provide consistency among inputs. While augmentation adds changes like rotation and flipping to boost data diversity and improve model robustness, normalization scales pixel values to improve model performance.

B. Classification Module

The system employs advanced AI and ML techniques, focusing on the classification module as its core component. For text analysis, a Bi-LSTM (Bidirectional Long Short-Term Memory) is utilized, addressing challenges like the vanishing gradient problem in training traditional RNNs over extended sequences. Bi-LSTMs are effective for tasks such as natural language processing, time series prediction, and sentiment analysis due to their ability to capture long-term dependencies and relationships in sequential data.

In disaster image recognition, computer vision techniques, specifically Convolutional Neural Networks (CNNs), are applied to analyze and classify images related to natural disasters, accidents, or emergencies. CNNs, an extended version of Artificial Neural Networks (ANNs), are tailored for structured grid data like images and video. They excel in computer vision tasks, including image classification, object detection, and image recognition. The CNN architecture includes layers like input, Convolutional, Pooling, and fully connected layers. Convolutional layers extract features, Pooling layers down sample images, and fully connected layers make final predictions. The network learns optimal filters through backpropagation and gradient descent.

C. Integration and Alert Generation Module

We can pass either type of data in the API (text or image). If both values are passed, then it generates an alert even if one of the conditions is true.

D. Deployment Module

To enable scalability and real-time responsiveness, the system is deployed on a cloud infrastructure, leveraging advanced features provided by leading cloud providers such as AWS. This cloud-based architecture is designed to optimize resource allocation, enhance cost efficiency, and offer significant workload flexibility.The cloud infrastructure includes a comprehensive architecture that integrates several key components. The system is hosted on a network of EC2 (Elastic Compute Cloud) instances distributed across multiple Availability Zones (AZs). This multi-AZ deployment ensures high availability and fault tolerance, as the system can seamlessly handle failures or outages in one AZ by redirecting traffic to other operational AZs.

Load balancing is a critical component of this architecture, facilitated by AWS Elastic Load Balancer (ELB). ELB distributes incoming traffic across multiple EC2 instances, which helps to maintain consistent performance and prevent any single instance from becoming a bottleneck. This dynamic distribution of traffic ensures that the system remains responsive and efficient even under varying load conditions. Auto-scaling is another pivotal feature employed in the system to adapt to changes in demand. By configuring AWS Auto Scaling, the system can automatically adjust the number of EC2 instances based on real-time traffic and workload. This means that during peak traffic periods, additional instances are launched to handle the increased load, whereas during off-peak times, instances are terminated to reduce costs.

Auto-scaling not only optimizes resource usage but also ensures that the system maintains high performance and reliability without manual intervention.Additionally, continuous system performance monitoring is integral to ensuring that the solution meets the demands of dynamic disaster scenarios. Tools such as AWS CloudWatch are used to monitor key metrics and set up alerts for unusual activities or performance issues. This proactive monitoring allows for immediate responses to potential problems and helps maintain the smooth operation of the system in real- time. Overall, the cloud-based architecture, with its multi-AZ redundancy, load balancing, and auto-scaling capabilities, provides a robust, scalable, and cost-effective solution for managing disaster scenarios efficiently and reliably. Overall, the cloud-based architecture, with its multi-AZ redundancy, load balancing, and auto-scaling capabilities, provides a robust, scalable, and cost-effective solution for managing disaster scenarios efficiently and reliably.

5. APPLICATION OF THE PROPOSED SYSTEM

Because the system allows for quick decision-making and real-time data processing, it has the potential to significantly change disaster response and management. Through the use of social media material, emergency responders can prioritize regions in need and distribute resources more efficiently by receiving early warnings and comprehensive situational knowledge. For dynamic disasters like wildfires or floods, the system's capacity to analyze large amounts of data fast is essential since it allows authorities to receive timely updates on shifting circumstances. This promptness can improve agency cooperation and response efficiency overall.

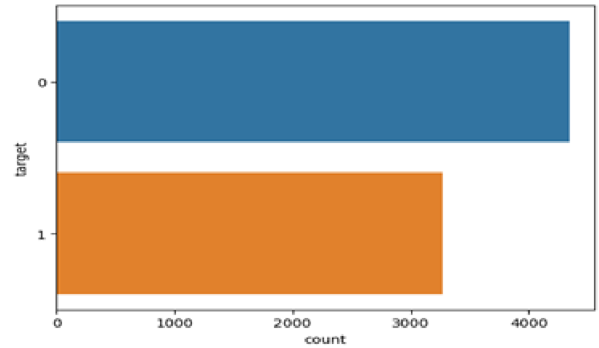

Figure 2. Representation of non-disaster and disaster tweets

The technology provides revolutionary uses for disaster management and response. Emergency responders can more effectively distribute resources and give priority to important locations when early warnings and comprehensive situational awareness are provided via real-time social media content analysis. Rapid data processing helps with dynamic disasters like floods and wildfires, boosting agency cooperation and increasing response effectiveness. With an emphasis on actionable information and a reduction in the amount of time needed for manual verification, the AI models accurately classify content linked to disasters. The system provides insights on the spread and impact of disasters, which helps with post-disaster analysis and recovery activities in addition to rapid response. Future preparedness planning and policy-making are informed by this data-driven approach, which eventually strengthens resilience against natural disasters. In terms of proactive catastrophe management, it is a major technological advancement overall.

6. EXPERIMENTAL RESULTS

The results were obtained while preprocessing the models. Figure 2 indicates that in the text categorization dataset, around 4500 tweets contain content unrelated to disasters, while approximately 3200 tweets are disaster-related. This dataset significantly aids in training the text categorization model. The distribution is crucial as it serves as the model's training dataset, exposing it to various linguistic patterns and contexts through a substantial representation of unrelated disaster tweets. This diversity enhances the model's ability to accurately distinguish and categorize text, thereby strengthening the system's overall resilience and effectiveness in identifying and responding to relevant social media information about disasters.

Graphs in Figure 3 present the top 10 keywords from the training set for disaster and non-disaster tweets, offering

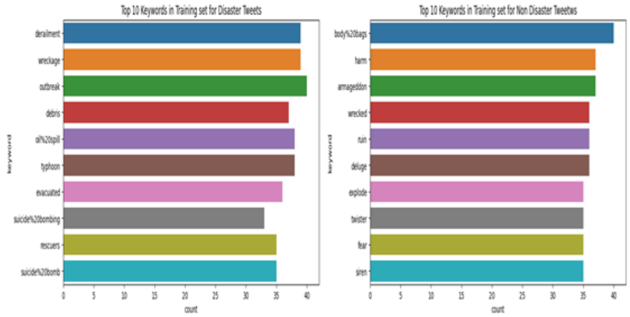

Figure 3. Depicts top 10 keywords in training dataset for disaster/non-disaster tweets

insights into linguistic subtleties and recurring themes. Keywords like "wreckage," "outbreak," and others are crucial for the model's understanding and predictions. These graphs serve as markers for distinct linguistic patterns related to disasters, aiding the program in learning contextual cues and distinguishing emergency-related tweets from unrelated ones. The identified keywords contribute to feature extraction, impacting the model's categorization decisions. The popularity of specific terms indicates semantic richness, enhancing the system's real-time tweet recognition and classification during emergencies. In summary, these graphs enhance accuracy and reliability by providing valuable insights into linguistic features of disaster-related tweets, enabling informed predictions in emergency scenarios.

The study illustrates the prominent locations in the training set for tweets related to disasters, featuring terms like "Mumbai," "Nigeria," "India," "Australia," and "Ireland." This insight into the geographic distribution of social media information on emergencies, as depicted in Figure 4 , is crucial. The prevalence of "India" and "Mumbai" suggests a higher frequency of disaster discussions in the South Asian region, while the mention of "Nigeria" underscores the significance of the African continent in these conversations. The inclusion of "Australia" and "Ireland" indicates that disaster-related content extends beyond regions prone to natural disasters. Analyzing these top areas helps customize disaster response plans based on geographic prevalence,facilitating resource allocation and focused preparation. Understanding the international distribution of disaster- related discussions is vital for fostering global cooperation and aid during crises. Consequently, these graphs serve as valuable resources for emergency responders, governments, and humanitarian groups, enabling a more sophisticated and location-aware approach to disaster management.

A. *Text Classification Model*

The Bi-Long Short-Term Memory (Bi-LSTM) model, a robust sequential neural network architecture, was designed for text classification in natural language processing applications. Unlike typical LSTM models, the Bi-LSTM processes information bidirectionally, considering both past

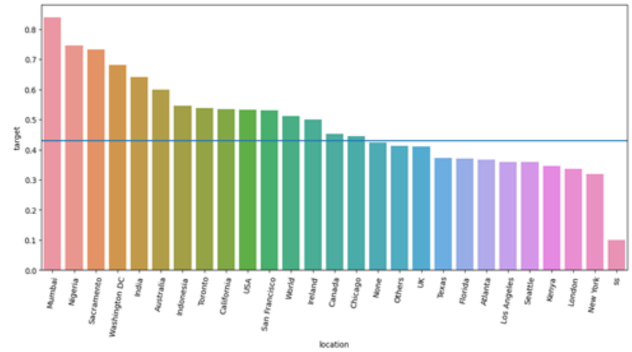

Figure 4. Represents top locations in the dataset for text classification

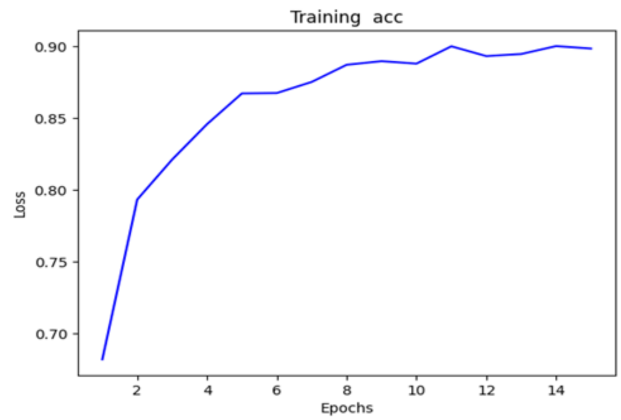

Figure 5. Training Accuracy Graph for Text Classification Model

and future context, particularly useful when a word's meaning relies heavily on its surrounding words. The model demonstrates its learning and generalization capabilities with an 87 percentage training accuracy and approximately 1.4 training loss. This indicates its effectiveness in capturing patterns and relationships within the training dataset, as evidenced by the high training accuracy and relatively low training loss in Figure 6 . The training accuracy

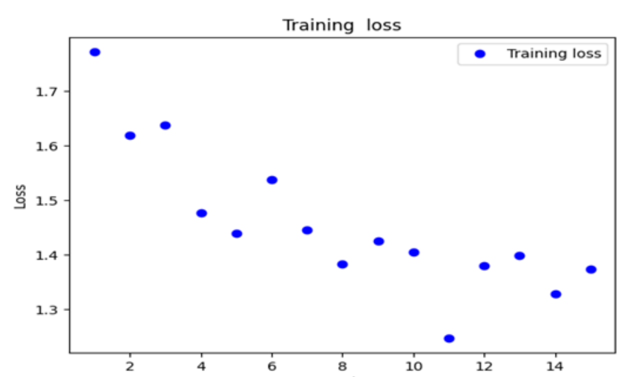

Figure 6. Training Loss Graph for Text Classification Model

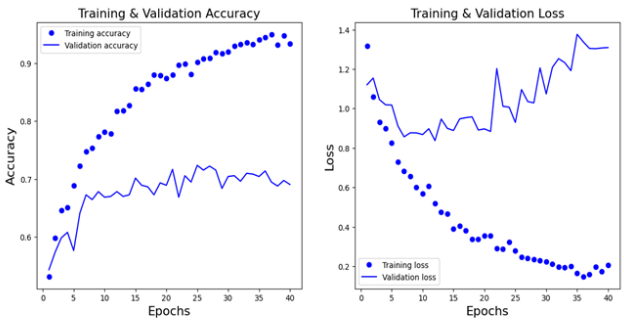

Figure 7. Training and Validation Graphs for Image Classification Model

graph illustrates the Bi-LSTM model's ability to distinguish between tweets related and unrelated to disasters. As accuracy steadily improves, the model's capacity to recognize complex pat- terns in text enhances, suggesting potential effectiveness with unobserved data. The training loss graph in Figure 6 complements the accuracy graph, showcasing the model's convergence during training by refining parameters and reducing errors. A smaller training loss implies more precise learning, reinforcing prediction accuracy. In summary, the Bi-LSTM model's relevance lies in its ability to comprehend the sequential nature of text data, making it suitable for text classification tasks. The training accuracy and loss graphs (Figure 5 and Figure 6) serve as crucial tools for model evaluation and refinement, offering insights into its functionality and potential real-world applications, especially in classifying disaster-related content on social media.

B. *Image Classification Model*

Convolutional neural networks, or CNNs, are a type of specialized deep learning architecture that are very useful for image classification applications since they are intended for processing and classifying visual data. Convolutional layers, which are part of its distinctive structure, filter and extract characteristics from images in a methodical manner, allowing the model to build hierarchical representations. Finally, fully connected layers combine collected characteristics for final predictions, whereas pooling layers reduce spatial dimensions. In computer vision applications including object identification, picture classification, and image recognition, CNNs have proven to perform remarkably well.

A CNN model is important for image classification because it can automatically extract hierarchical feature representations from images, identifying both fine-grained details and broad patterns. CNNs are highly suited for a variety of picture classification applications because of their ability to recognize complicated visual patterns thanks to hierarchical feature learning. CNNs have completely changed computer vision applications, and they are now essential in areas like facial recognition, autonomous cars, and medical imaging.

Figure 7 . Showing the model's performance on the training dataset, the training accuracy graph reaches a remarkable 93 percentage. This suggests that CNN has successfully acquired the ability to categorize images from the training set. The validation accuracy graph, on the other hand, indicates that the model would have trouble generalizing to fresh, untested data due to its reduced accuracy of 70 percentage. A large discrepancy between the accuracy of training and validation runs the risk of overfitting, in which the model becomes excessively specialized to the training set and has trouble processing a variety of images. To resolve this gap, other augmentation or regularization solutions could be investigated. Training Loss and Validation Loss Graph in Figure 7 shows how the loss decreased during training, eventually reaching 20 percentage, which suggests efficient convergence and error reduction. Simultaneously, the validation loss graph shows how effectively the model generalizes to new data, with a value of 1.4. The relatively low validation loss indicates that the CNN model continues to perform well on validation data in addition to learning from the training set. This shows that the model can produce precise predictions on novel photos.The high training accuracy demonstrates how well the CNN can identify complex patterns and details in the training set. To make sure the model can be applied to a variety of photos, a closer look is necessary given the reported discrepancy between validation and training accuracy. The model's effectiveness in reducing mistakes during training and effectively transferring to fresh data is further supported by the training and validation loss graphs. These graph-derived insight through Figure 7 steer the iterative CNN model refining process, which may include tweaking hyperparameters, augmentation approaches, or regularization procedures to improve the model's overall performance. These visualizations are important for more than just evaluating the model; they are also essential for refining and fine-tuning the CNN architecture to increase accuracy and dependability in image classification jobs.

C. *Importance of the System In Different Disaster Scenarios*

The study offers a strong artificial intelligence (AI) disaster management solution that makes use of social media networks' text and visual data. The architecture of the system, which is hosted on AWS, enables real-time categorization and analysis, which is essential in catastrophe scenarios that are changing quickly. The CNN model achieves 93 percentage accuracy in image classification, while the Bi-LSTM model achieves 87 percentage accuracy in text classification. These results show that the system performs well in identifying pertinent disaster content. The system can swiftly recognize posts signalling structure damage or human misery in situations like earthquakes. For example, tweets including photographs of crumbling structures or keywords like ”earthquake” and ”rescue” set off notifications that allow for quick action. The system's capacity to handle massive amounts of data effectively is essential since social media activity following an earthquake frequently spikes. The system's picture classification can successfully detect regions that have flooded and sustained water damage during floods. Real-time updates on rising water levels or evacuation requests can also be captured through text analysis. This feature guarantees that emergency services get information in a timely manner so they can deploy resources efficiently.

When it comes to wildfires, the text analysis gathers data on the afflicted locations and the spread of the fire, while the CNN's accuracy helps identify photographs of smoke or flames. Because the system is running on cloud infrastructure, it can handle sudden increases in data volume as events develop and stay responsive and scalable.

7. ETHICAL CONSIDERATION RELATED TO DATA PRIVACY

The use of Kaggle datasets which is open source, for disaster management raises ethical issues that are discussed in this research. As social media content is frequently included in Kaggle data, concerns about consent and privacy are common. One more thing to worry about is data bias. It's possible that Kaggle datasets don't fairly reflect a range of demographics, which can produce biased findings. In the event that the dataset predominantly comprises data from particular locations or demographics, the model's performance might be enhanced for those groups while potentially disregarding others. This could lead to unequal resource allocation and catastrophe response.

The efficacy of the system as a whole may suffer if the training data has a higher concentration of instances of a particular disaster or region. This is because the models may not generalize as effectively to fewer represented scenarios. Trust must be upheld by ensuring transparency in data processing and decision-making. It is important to let stakeholders know about the system's features and limitations. The study advances the responsible application of AI and cloud computing in disaster management by addressing these ethical issues.

8. CONCLUSION

By utilizing cutting-edge Artificial Intelligence (AI) and Machine Learning (ML) techniques to develop a comprehensive system for real-time disaster classification of social media data, this research represents a significant turning point in the field of disaster management. The models we have deployed, the Convolutional Neural Network (CNN) for image classification and the Bi-Long Short-Term Memory (Bi-LSTM) for text classification, have demonstrated remarkable performance. The Bi-LSTM model exhibits strong pattern recognition in textual data, with a training accuracy of 87 percentage and a training loss of around 1.4. Concurrently, the CNN model highlights its ability to extract complex features from images with training accuracy of 93 percentage, validation accuracy of 70 percentage, training loss of 20 percentage, and validation loss of 1.4. Our disaster classification method is based on these models, which offer sophisticated insights into the types of social media content relevant to disasters.

Our knowledge is enhanced by the spatial analysis of the top locations, which reveals hotspots that are commonly linked to discourse connected to disasters. The inclusion of places like "Mumbai," "Nigeria," "India," "Australia," and "Ireland" highlights how global these conversations are, providing insightful information for developing customized disaster response plans, allocating resources efficiently, and encouraging cross-border cooperation in times of crisis.

However, there have been difficulties with the research and ethical questions have been raised. While improving functionality, the integration of free APIs for content identification necessitates a careful assessment of reliability across various disaster situations. Responsible AI implementation is essential, as ethical concerns about data collecting, privacy preservation, and disinformation mitigation highlight.

This research is important for reasons other than just creating a novel framework for categorizing disasters. It adds to the conversation about the responsible use of AI and ML in disaster relief. The system can have a huge impact on prompt and well-informed decision-making during emergencies, enabling responders and communities to become more resilient and prepared. The addition of email alerts gives our system much more relevance. The Telegram API's real-time alert creation feature guarantees that pertinent stakeholders receive vital information on time. This functionality greatly improves our system's usefulness in real-world circumstances by enabling quick reactions. Moreover, the system's operational efficiency is enhanced by the implementation on the Amazon Web Services (AWS) platform, which comes with load balancing and auto-scaling features. The implementation of AWS guarantees scalability, affordability, and instantaneous response. Load balancer integration maximizes resource allocation, and auto-scaling makes sure that systems can adjust to changing workloads. This infrastructure improves our system's performance and dependability, which increases its efficacy in actual crisis situations. In summary, this study demonstrates the revolutionary possibilities of artificial intelligence and machine learning in the field of disaster relief. It emphasizes how crucial it is to find sensible, open, and practical answers when negotiating the tricky terrain of crisis management. In the future, continuous cooperation with stakeholders, legislators, and subject matter experts will be necessary to improve the accuracy, moral compliance, and usefulness of the system.

As demonstrated by our email alert system and AWS deployment, the combination of cutting-edge technologies, moral considerations, and sturdy infrastructure will continue to shape the course of innovation in disaster management and promote a more responsive and resilient international community. This work establishes a strong basis for future developments in the area of social media disaster classification using AI and ML. Numerous opportunities arise for more investigation and enhancement, guaranteeing the ongoing development and influence of the suggested framework.

9. CHALLENGES AND LIMITATIONS

There are a number of obstacles and restrictions when implementing the AI-based disaster classification system in practical situations. Ensuring the system's scalability and dependability at peak periods, such big disasters when social media activity rises, is a huge concern. This means that in order to manage abrupt spikes in data volume without sacrificing performance, reliable cloud infrastructure and effective load balancing are needed. Compliance with laws like the GDPR and data protection are essential. Given the variety of sources of social media information, the system must guarantee that user data is anonymized and treated ethically, which can be challenging.

Another drawback is bias in the training set. There may be differences in the efficiency of responses across scenarios if the data used to train the models is not representative of all populations or types of disasters. The quality and relevance of incoming data are critical for effective classification and real-time processing. Social media noise and false informat¬¬ion might impair the system's capacity to produce trustworthy alerts, requiring sophisticated filtering and validation procedures.

Logistical difficulties arise when integrating the system with current emergency response frameworks. In order to guarantee that the system's outputs are applicable and consistent with existing procedures, collaboration with many agencies is necessary. Ultimately, even if the system can improve reaction to disasters, resolving these issues is essential to its deployment and effective use in actual circumstances.

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