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)

I. INTRODUCTION

The abundance of real-time information released during emergencies and catastrophes has turned into a priceless resource for disaster management and response in an era characterized by the pervasive influence of social media. This content can take the shape of text, and photographs. However, typical response methods face substantial hurdles due to the dynamic and unstructured nature of this data. By creating and deploying a cutting-edge artificial intelligence (AI) and machine learning (ML) system for the real-time classification of social media information relevant to disasters, our research aims to close this gap.

Through an emphasis on several data modalities such as text, photographs, this project aims to offer a thorough comprehension of the catastrophic scenario as it unfolds. In order to improve the system's accuracy and adaptability to various crisis scenarios, open APIs for image recognition, and natural language processing have been integrated. This adds a layer of complexity and functionality to the system.

II. CHALLENGES PRESENT IN THE EXISTING SOLUTIONS

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.

III. RELATED WORK

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. RaVÇn, 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 [4]. 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 [3, 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, 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, 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%, 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% 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].

IV. PRPOSED SYSTEM

In the initial stage (see Fig 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.

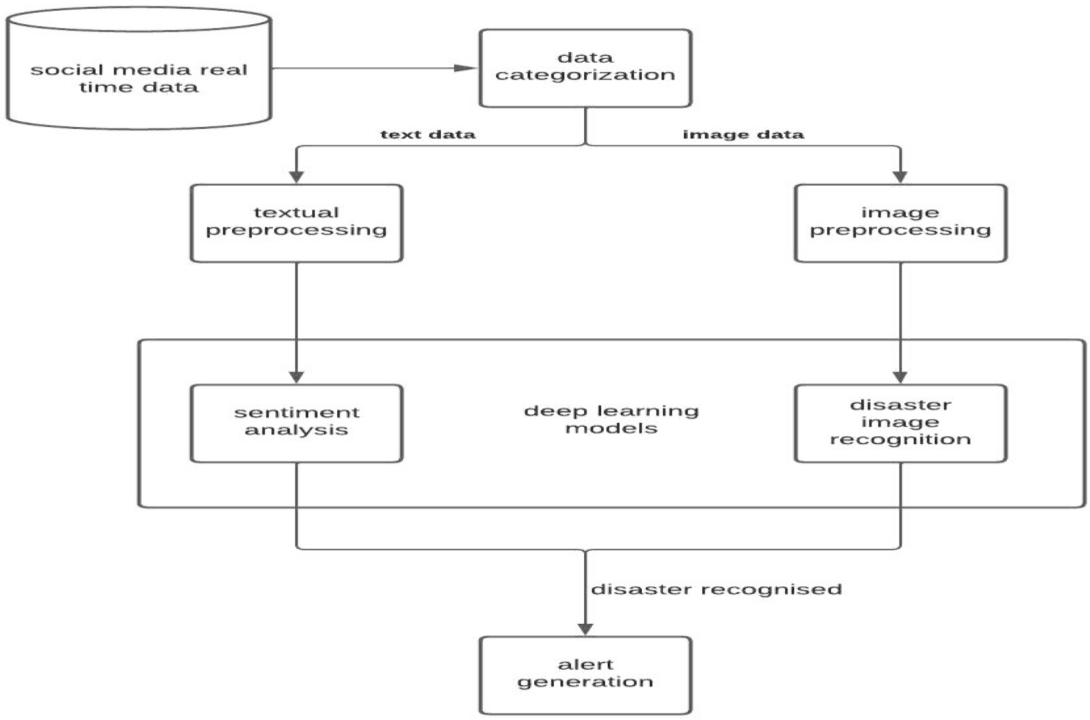

Fig. 1 Proposed System Architecture

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 Module:*

The project's primary goal at the outset is to gather real-time data from social media sites. Using Kaggle, the system obtains the text and image data for preprocessing and training the model. This step makes sure the dataset is up to date and accurately captures the dynamic nature of social media material during emergencies.
The data preparation submodule seeks to improve data quality concurrently. Important procedures removing noise and irrelevant information, and formatting issues (text, pictures). Involves converting the text to lowercase for consistency, removing duplicate texts, removing links, and emojis etc. This procedure handles the difficulties posed by unstructured and diverse data types while laying the foundation for further analysis.

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 downsample images, and fully connected layers make final predictions. The network learns optimal filters through backpropagation and gradient descent.

C. *Integration and Alert Generation Module:*

The integration module combines the outcomes of the various methods of classification. A single framework using API for decision-making is created by the system through the integration of insights from text, and graphics. This stage is essential because various data kinds provide distinct viewpoints that help us understand the crisis scenario holistically.

The smooth integration of the email notifier is also present in the submodule responsible for alert production. This makes it possible to automatically generate alerts based on pre-established criteria, guaranteeing that pertinent stakeholders receive vital information on time.

The sample GET API –

API Path - /classify_disaster

{

“text”: <sample_text>

“image”: <image_file_path>

}

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. *Deployement Module:*

To enable scalability and real-time responsiveness, the system is deployed on a cloud infrastructure in the last stage. Selecting a cloud configuration from reputable providers like as AWS allows for effective resource allocation, cost efficiency, and workload flexibility.

Continuous system performance monitoring guarantees that the implemented solution meets the demands of dynamic disaster scenarios and runs smoothly in real-time. We have deployed the API using EC2 instance in multiple availability zones, with auto scaling enabled, so that in case of high or low traffic, the application can up-scale or down-scale the servers accordingly and optimize the cost.

V. EXPERIMENTAL RESULTS

The results were obtained while preprocessing the models. Fig 2 indicates that in the text categorization dataset, around 4500 tweets contain content unrelated to disasters, while approximately 3200 tweets are disaster-related.

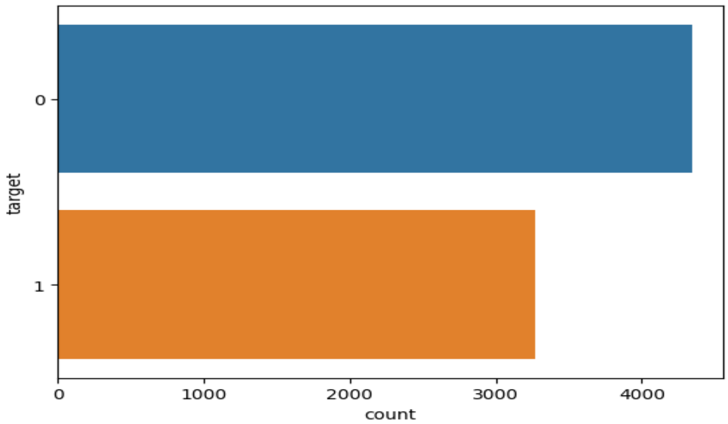

Fig. 2 Represents the non-disaster and disaster tweets

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.

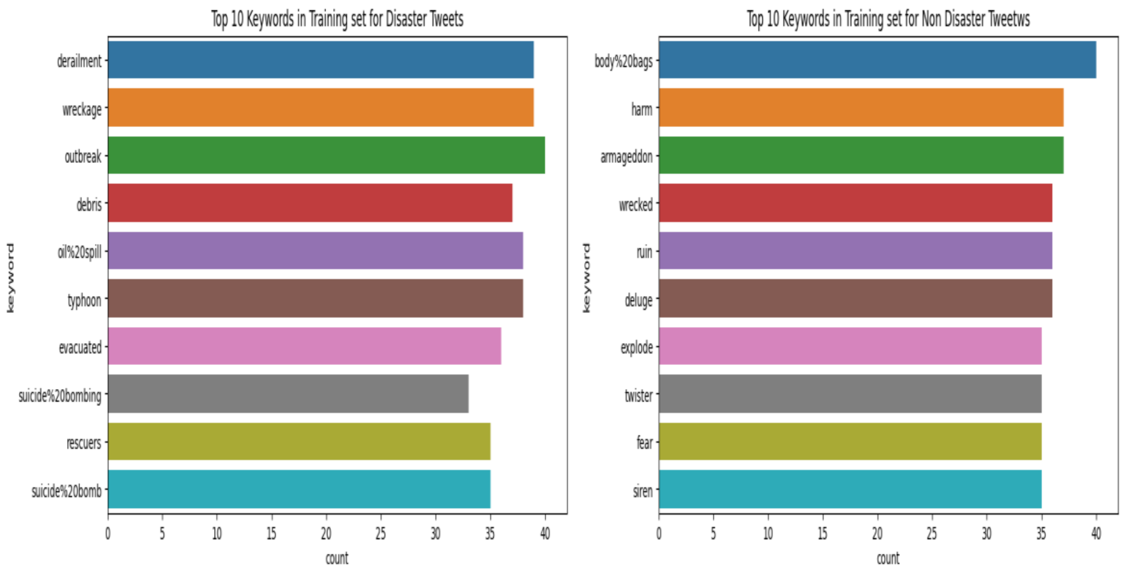

Fig 3: Depicts top 10 keywords in training dataset for disaster/non-disaster tweets

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

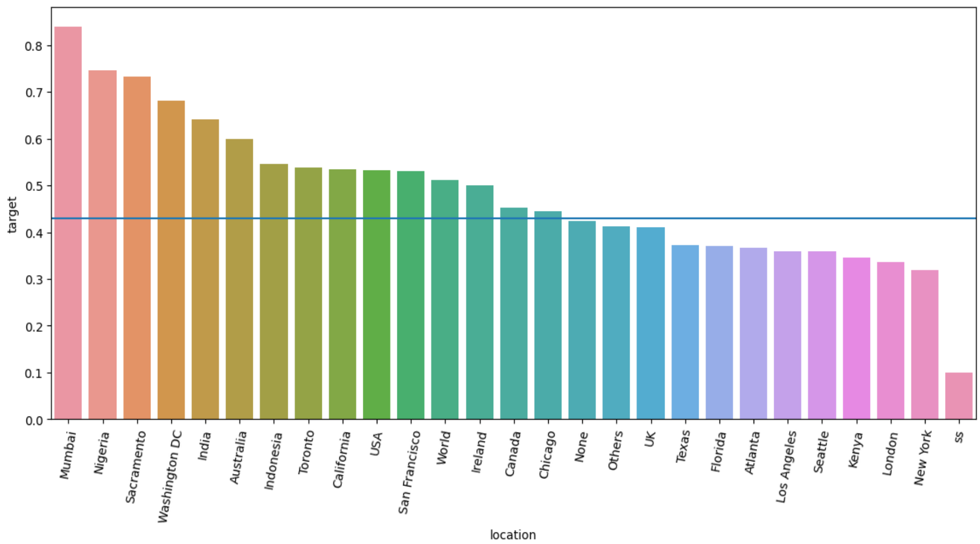

Fig 4: Represents top locations in the dataset for text classification

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 Fig 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:

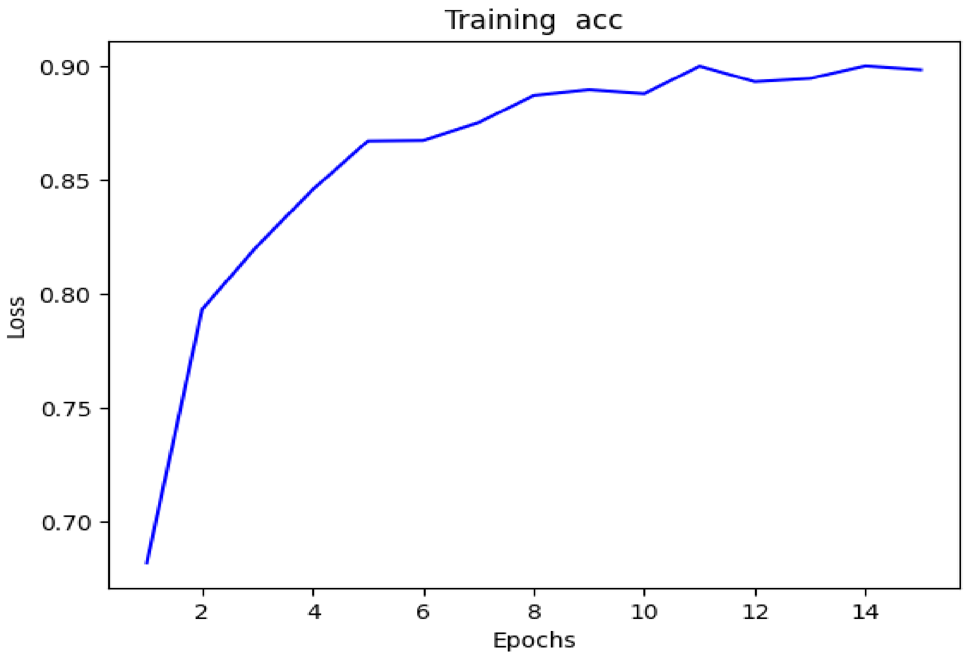

Fig 5: Training Accuracy Graph for Text Classification Model

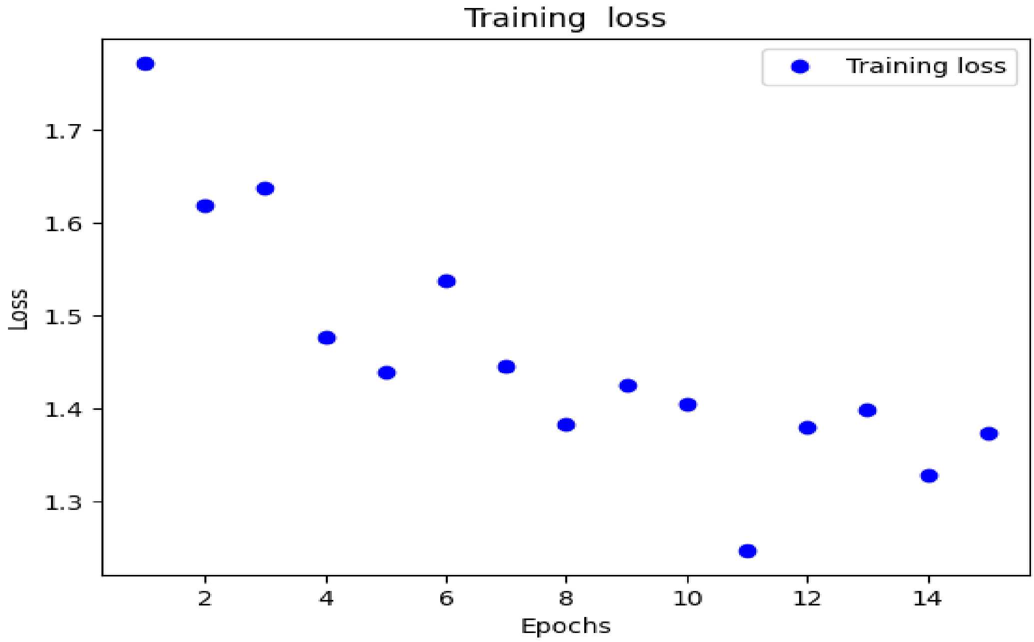

Fig 6: Training Loss Graph for Text Classification Model

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 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% 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 fig 6. The training accuracy 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 patterns in text enhances, suggesting potential effectiveness with unobserved data. The training loss graph in fig 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 (fig 5 and fig 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:*

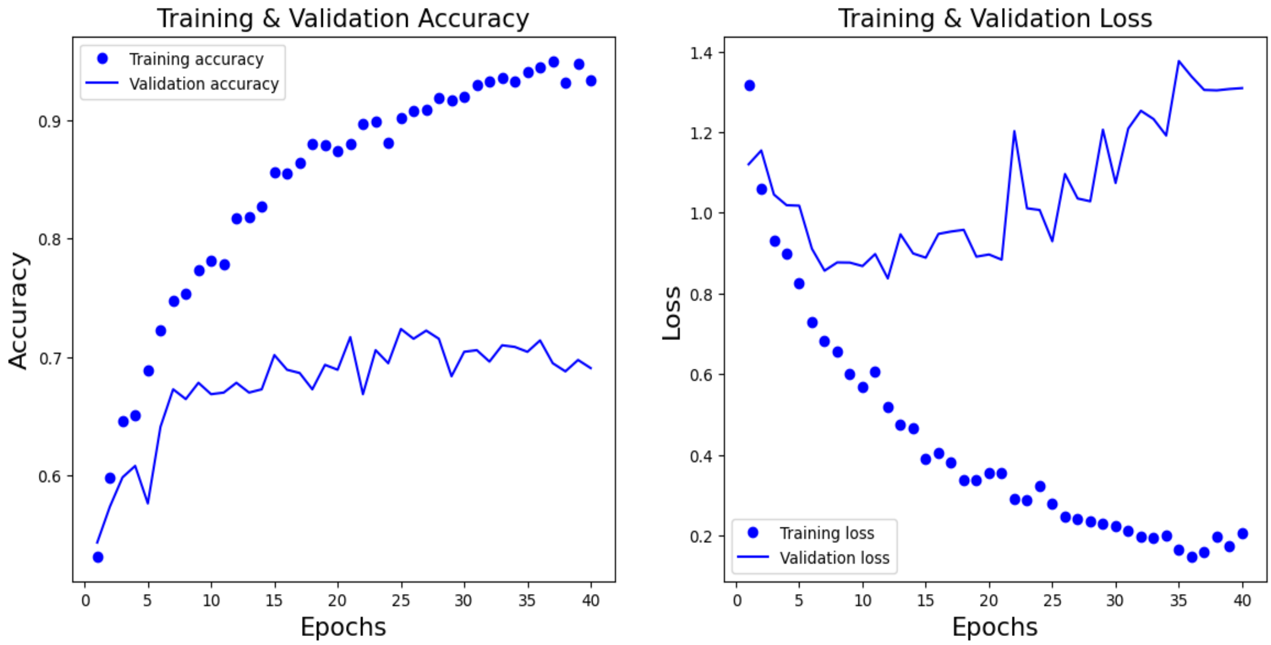

Fig 7: Training and Validation Graphs for Image Classification Model

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.

Fig 7. Showing the model's performance on the training dataset, the training accuracy graph reaches a remarkable 93%. 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%. 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 fig 7 shows how the loss decreased during training, eventually reaching 20%, 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 fig 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.

VI. 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% 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%, validation accuracy of 70%, training loss of 20%, 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.

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