Disaster Management With Sentiment and Earthquake/ Tsunami Prediction System

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***Abstract*—Identification of relevant disaster information from social media and online news feeds is essential for early warning and emergency response. This paper introduces a Disaster Response and Alert System with a hybrid Natural Processing (NLP) approach that classifies short-text messages into disaster categories. This proposed Disaster Response and Alert System incorporates a Long Short-Term Memory (LSTM) network approach for contextual and sequential analysis of texts. This approach is further enhanced through a Random Forest algorithm that uses TF-IDF for lexical validation. This proposed Disaster Response and Alert System uses Random Forest algorithms that further provide probabilistic support to improve confidence levels. To determine alert activation of disaster classes such as Earthquake, Flood, Cyclone, and Tsunami, a confidence level approach is used. This study is implemented as an interactive Streamlit web application that facilitates real-time text message prediction and analytical assessment. Analytical assessment is further evaluated through a confusion matrix approach that ensures both deep learning and machine learning approaches are effectively used to classify texts related to particular disaster classifications. This study introduces a hybrid approach to effectively identify and classify texts through hybrid models of Natural Processing.**

Keywords—Disaster Prediction, Natural Language Processing, LSTM, Random Forest, Text Classification, Early Warning System, Social Media Analytics.

I. INTRODUCTION

The increasing popularity of social media platforms and news portals has altered the landscape of information diffusion related to natural disasters. In times of critical events like earthquakes, floods, cyclones, and tsunamis, people actively disseminate real-time information. [1] These provide important hints about early-stage awareness. However, due to their unstructured, noisy, and high-volume nature, these text based prevailing opinions cannot be tracked in an efficient and reliable manner. For this reason, there is increasing interest in using automated Natural Language Processing techniques for text analysis related to disasters. Recent advances in machine learning and deep learning have made it feasible to efficiently find meaningful patterns from short sequences. LSTM deep architectures for capturing contextual patterns from text are well-proven, while conventional machine models like Random Forests prove efficient for discriminative feature extraction. However, due to dependencies on simple models, these still have certain limitations in robustness and generalization capabilities, particularly when fed sparse or confusing text inputs. [2]. To overcome these issues, this paper puts forth a hybrid model for disaster text classifiers, combining LSTM-based semantic modeling and Random Forest feature validation. The model is designed and implemented in an interactive prototype system with real-time predictive outcomes.

II. PROBLEM DEFINITION

A crucial issue related to disaster management and real-time support systems for disaster response is the effective identification of events related to a disaster in textual information. Web posts and news articles on social media are effective sources of early notifications related to natural disasters;[3] however, information is extremely loosely and noisily textured and context-sensitive. Textual information is associated with possible inconsistencies in terms of word usage (colloquial), incomplete information description, vague terms, and non-disaster information. In other words, there are challenges related to effective classification using rule-based classification systems.[4] In addition, utilizing a single machine learning model is not an effective method due to inconsistencies in model sensitivity and awareness of contextual information. Typically, existing support systems typically show high false alarm rates or are late to recognize disasters and offer generalized information for different types of disasters.[5] There is a need to design a support system for automatic and effective differentiation of disaster information and non-disaster or general information. The support system should additionally offer confidence measures for effective alert generation. The issue being addressed is related to disaster. Moreover, posts related to disasters very often contain mixed emotions, sarcasm, ambiguity in location, and incomplete context, which further increases misclassification.

III. EXISTING WORK

In the early stages of disaster detection using research, the focus was mainly on using keyword filtering techniques to search for disaster-related posts within the social media feed. Although these methods presented low computational complexities, they had numerous false positives due to the use of ambiguous language.[2] Later, traditional machine learning methods such as Naïve Bayes, Support Vector Machines, and Random Forests were proposed. These methods used hand-crafted feature representations such as the Bag-of-Words model and TF-IDF to achieve disaster detection. However, these models were not successful in handling the semantic relationships between words in the informal posts.[6]The latest research has focused on deep architecture designs like Convolutional Neural Networks and Long Short-Term Memory Networks for the representation of sequence and context information for disaster-associated texts.

Despite the linguistically varying nature of texts being handled effectively, a need for a significant number of tagged examples and a possible overfitting issue were some challenges.[7] A combination of deep learning and traditional classification has also been discussed to increase robustness; yet, current systems are not much effective for real-time alerts.

IV. PROPOSED WORK

This study presents a hybrid disaster-related text classification system developed through Natural Language Processing and machine learning. The system takes short-text inputs such as social media posts and/or news and identifies the respective disaster type.[9] It uses a deep learning LSTM network to extract the context-related semantic information from tokenized forms of input short texts. Simultaneously, a TF-IDF-based Random Forest classifier is utilized to perform a token-level validation process for each input by deriving a set of class probabilities.[3] The predictions from both networks are combined through a confidence-based fusion technique, wherein a Random Forest-based confidence mechanism is utilized to reinforce predictions from the LSTM network if a pre-determined level of consensus is achieved. Thematic confidence values are utilized to trigger alerts and avoid non-critical alerts. The study utilizes Streamlit for creating an interactive application that offers real-time predictions and visualization of confidence and analysis through a confusion matrix. The model has been developed to work as a supporting tool for disaster awareness in the early stage and is not designed for a complete automated alert system.

V. LITERATURE SURVEY

There has been an increasing trend in recent research on disaster response related to the modeling of disaster dynamics, system resilience, and joint decision-making. Research initiatives like those found in Li et al. [1] and Rodriguez-Espindola [5] delve into analytical and simulation models to better comprehend the spreading of the disaster as well as multi-period decision-making within complex engineering and techno-social settings. These studies use scenario-based hybrid networks and optimization models to determine the effects of the disaster and the use of resources during simultaneous or dynamic settings. In a similar vein, other research initiatives like those of Diaz et al. [6] provide simulation-based models to analyze the aftermath of housing reconstruction during the disaster, stressing the importance of predictive models for disaster resilience over the long term.

Though these models establish important theoretical foundations on which the impact of the disaster can be analyzed, they remain dependent on structured information and scenario-based frameworks, which remain sluggish to real-time information streams from social media platforms and online postings. There thus remains a divide between system models of the disaster and real-time awareness during the early stages of quick disaster detection and situational analysis. The other significant stream of literature relates to communication infrastructure networks and communications for disaster response/management. Literature such as Karaman et al. [2] provides a broad review for disaster communication systems with a focus on sustainable designs that would ensure communication in disaster situations. Literature like Manuel et al. [3] & Fujisawa et al. [7] focus on LoRa networks as well as drone-assisted communication concepts for supporting SAR activities & emergency communications in large-scale disasters. Chen et al. [9] further discuss space–air–ground-integrated networks (SAGIN) as a universal communications framework for disaster situations. These reviews demonstrate the impetus of effective communications in disaster mitigation but concentrate only on the communication & network infrastructure means. These pieces of literature are not related to automated interpretation of disaster-relating information from affected people. Therefore, communications frameworks are effectively used for transmission of information from the above literature. The focus of these communications frameworks lacks intelligent interpretation of textual information intended for information translation from unrefined information to actionable alerts for disaster decisions. The emergence of UGC has driven interest in social sensing and intelligent data analysis for disaster response.

A thorough survey of social sensors is offered by Shi et al. [4], which shows how social media can be harnessed as a distributed sensor during natural disasters. Risk communication dynamics on social media platforms have also been investigated by Momin et al. [16], who showed how information diffusion dynamics and message switching patterns affect perceptions during disasters. More recent models such as GeoDisasterAINet presented by Raju et al. [14] and the geospatial-AI model presented by Saleem et al. [15] make use of explainable AI and spatial techniques to improve disaster classification. However, many models have adopted architectures that are too complex or require copious amounts of data or geospatial dependencies that are inconvenient to deploy. Many models have also focused on offline analysis instead of real-time confidence-based classifications amenable to low-cost decision support systems Finally, disaster mitigation enabled by IoT and intelligent automation have been explored in enhancing the operational responses. Ahn et al. present how IoT devices may autonomously trigger safety during earthquakes, while Liu et al. focus on post-disaster restoration in the power grid enabled by cyber–physical coordination and 5G communications.

Xu et al. investigate semantic communication via unmanned aerial systems in a post-disaster scenario, while Teoh et al. apply deep learning-based object detection to flood response. [12] Despite these, most existing systems focus on physical sensing, infrastructure recovery, or visual data processing, with minimal attention to lightweight textual disaster classification systems that couple semantic understanding with probabilistic validation. This calls for hybrid natural language processing frameworks that integrate deep learning and classical machine learning models to provide real-time confidence-driven disaster awareness using unstructured text data.

VI. METHODOLOGY

The disaster management framework, as proposed, has been designed as a hybrid text-based classification system that effectively incorporates deep learning and classical machine learning models in the identification of disaster-related events from unstructured textual data. The methodology encompasses five major stages: data preparation, text representation, model training, hybrid prediction and confidence fusion, and finally system deployment with evaluation.[11] In general, the approach aims at exploiting the complementary strengths of sequential semantic learning and statistical feature-based classification to enhance robustness and reliability in disaster detection.

1. *Data Preparation and Preprocessing:*

The module (as figure 1) This system operates on small fragments of text, like social media posts or news snippets, which are naturally noisy and unstructured. The dataset is labeled into multiple categories: earthquake, flood, cyclone, tsunami, and normal (a non-disaster class). [12]Preprocessing text data cleans and normalizes it to minimize inconsistencies due to the informality of social network messages. Text data was then tokenized into a numerical sequence format understandable by deep learning models. In the case of classical machine learning, the text corpus was converted into numeric feature vectors with TF-IDF, which captures the importance of discriminative words while suppressing commonly occurring terms.[13] The dataset was divided into training and testing subsets to enable unbiased model performance evaluation.

2. *LSTM-Based Semantic Modeling:*

A Long Short-Term Memory (LSTM) neural network is used as the basic model for semantic analysis of the text relevant to the disaster. LSTMs are considered appropriate for modeling sequential data because they have the ability to learn dependencies at different distances. In the proposed framework, the text token sequences are padded to have the same fixed length for uniformity.[[14] The LSTM neural network model will analyze the text token sequences to generate class-specific probability scores for the various classes of the disaster. In this model, the linguistic patterns that are very subtle are analyzed to identify the semantic variations beyond the keyword search method. The class with the maximum probability is chosen for the preliminary designation of the type of disaster, along with the confidence level.

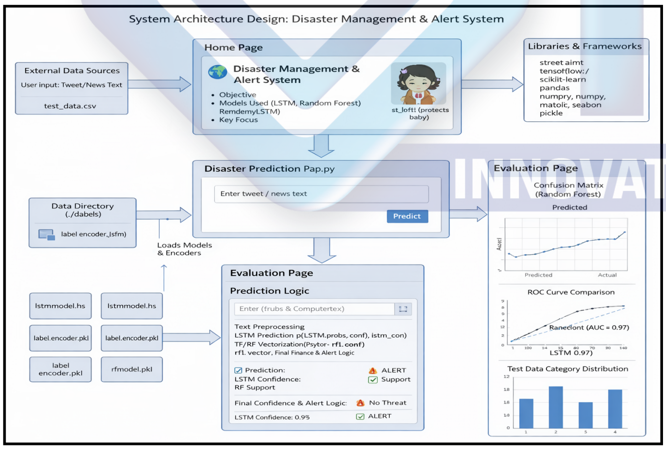

Figure 1. System Architecture Diagram

3. *Random Forest–Based Lexical Validation:*

In an attempt to make the deep learning model more robust, the Random Forest classifier is introduced to the framework. The Random Forest classifier is implemented to validate the model. The classifier works with the feature vector representing the TF–IDF. The input text will have class probabilities returned by the classifier to validate the results of the LSTM model.[15] The Reason for selecting the classifier includes the fact that it resists the problem of overfitting. Overfitting occurs when the model is too complex for the model to learn. The model is capable of working efficiently when the number of dimensions is high. The results will be easy to interpret due to the probabilistic results.

3.1 Hybrid Prediction and Confidence Fusion Strategy:

This is the major contribution of the proposed methodology comes from the hybrid prediction approach that uses the results from the LSTM and the Random Forest models.[9] LSTM results are used for the major classification since they have better semantic intelligence. Then, the Random Forest model uses its results to indicate the probability of the same result from the model or from the words. In the confidence fusion approach applied in the proposed methodology, a weighted average of the confidence values from the LSTM and the Random Forest models can be obtained.[10] However, if the Random Forest confidence level goes below a specific support level threshold, the method can solely depend on the confidence from the LSTM.

3.1.1 Notification Threshold Detection Applies to sensitive components:

From (figure 1) To facilitate effective disaster awareness, the proposed system includes class-specific alert threshold values. The disaster classes are assigned a confidence threshold based on observations to set the alert threshold. For the final confidence value above the threshold and the predicted classes assigned to the disaster classes, the proposed system issues an alert for the potential disaster event. The non-disaster input is processed with a high threshold to eliminate the false alerts. The decision logic based on the threshold is effective for making early decisions.

3.2 System Deployment and Evaluation Understanding System Deployment:

The entire framework is developed as an interactive web-based application with the help of Streamlit.[14] The entire model is properly supported for real-time text input, prediction, as well as confidence levels. The model is loaded in an optimal manner with the help of resource caching for efficient execution of the model. The evaluation of performance is completed with the help of a confusion matrix, which is determined on the basis of testing data.[2] The proposed approach is developed as a prototype system representing the effectiveness of the hybrid models for the classification of disaster text, as explained above.

VII. RESULTS

The Figure 2 depicts the Home page interface of proposed Disaster Management & Alert System developed using the Streamlit library. The interface has been created for giving a clear idea of what the system does before using any prediction/evaluation modules. A sidebar has been added for hassle-free access to Home, Disaster Prediction, and Evaluation pages.

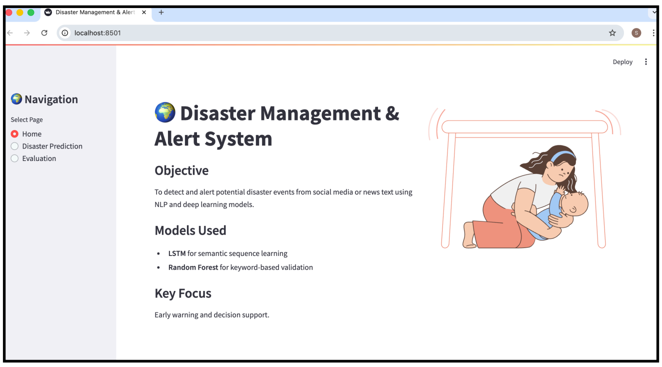

Figure 2. Disaster management UI

The interface clearly displays the name of the system in a large display field with a description of the objective of the system. The system's aim particularly concentrates on recognizing possible disaster events through social media posts & news using Natural Language Processing. The system highlights the use of two different learning models. The first model used is the LSTM model for semantic sequence learning. The other model used would be the Random Forest classifier for validation using keywords for added accuracy of prediction. The critical aim of the proposed system has been mentioned.

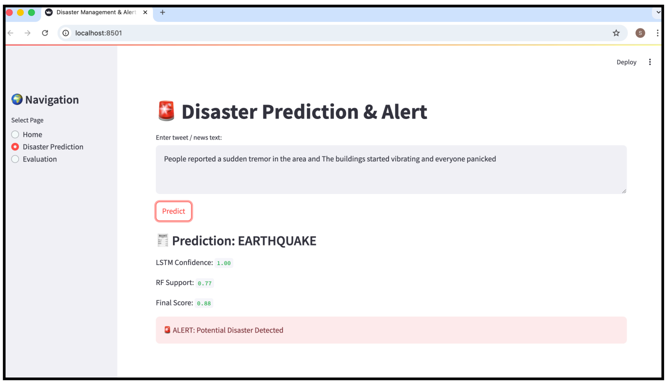

Figure 3. Disaster Prediction: EarthQuake

Figure 3 shows the Disaster Prediction and Alert interface of the proposed Disaster Management & Alert System. This interface provides users with the capability of inputs in the form of short texts obtained from social media or news regarding possible disaster scenarios. Upon user input, the System uses the hybrid Natural Language Processing approach for real-time text processing. A deep-learning algorithm with an LSTM approach analyzes the semantic and contextual aspects of the input text. However, the Random Forest Classification approach verifies the result with TF-IDF Lexical Features. Depending upon the result obtained from both approaches, the corresponding disaster type along with the confidence scores obtained from both approaches and an overall confidence score is displayed. Depending on the threshold values of respective disasters, the result decides whether an alert message needs to be activated. In the above figure, an input describing strong structural vibration triggers the activation of an alert message for an earthquake disaster.

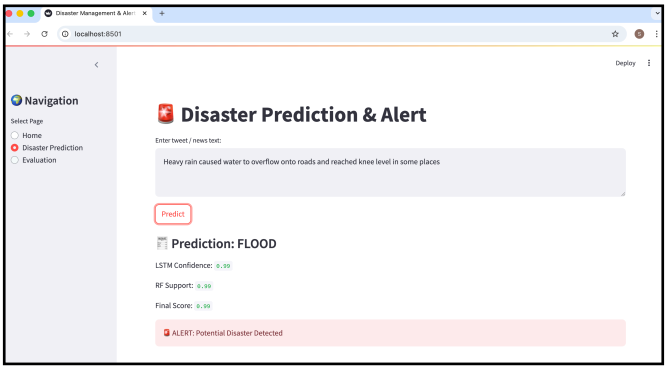

Figure 4. Disaster Prediction:Flood

From Figure 4 presents the Disaster Prediction and Alert interface of the proposed system during the processing of a flood-related input text. This module allows the user to provide small textual descriptions received from social media posts or news updates about heavy water accumulation affecting vehicles that are on the road. In this case, after clicking the predict button, the input text is analyzed using the proposed hybrid Natural Language Processing framework. The deep learning model based on LSTM performs semantic sequence analysis to identify context-dependent cues for the flooding context, whereas its prediction gets validated through keyword representation using TF-IDF by the Random Forest classifier. Accordingly, the predicted category (FLOOD) is reflected with an LSTM confidence score, Random Forest support value, and final aggregated confidence score of 0.99. The system identifies that the situation is a potential disaster with pre-defined class-specific confidence thresholds and raises a visual alert message.

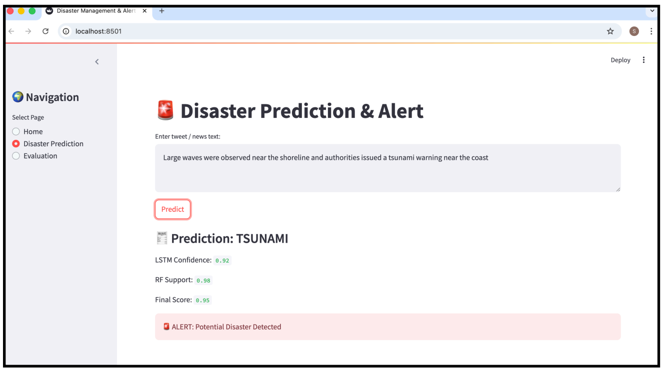

Figure 5. Disaster Prediction: Tsunami

Figure 5 shows the Disaster Prediction & Alert module reveals how the proposed hybrid prediction framework can be successful by analyzing real, time textual inputs such as tweets or news reports. Here the system is shown to take a sample input mentioning the unusual coastal activity and successfully classifies it as a TSUNAMI event. The Long Short, Term Memory (LSTM) model identifies contextual and sequential patterns in the text and gets a confidence score of 0. 92, which means the model has a good understanding of the language used in the disaster. Meanwhile, the Random Forest (RF) classifier characterizes the text features and delivers a confidence of 0. 98, thus, strengthening the prediction via ensemble learning. A final combined score of 0. 95 is attained by mixing both model results, thereby, facilitating trustworthy decision, making. With that much confidence, the system launches an automated warning for a possible disaster. Such outcomes confirm that the fusion of deep learning and machine learning models is beneficial in terms of increasing prediction accuracy, decreasing the number of false alarms, and allowing prompt disaster alerts for efficient emergency response.

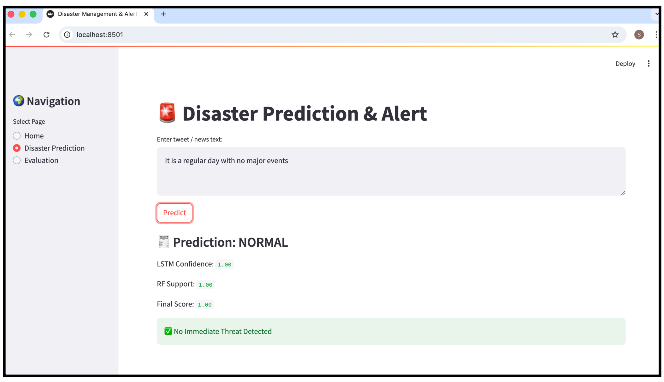

Figure 6. Disaster Prediction: Normal

The figure 6 demonstrates how well the system is able to differentiate between disaster, related and non, disaster, related texts and thus not to issue an alert unnecessarily. Here the text input is about a normal situation and gives no signs of any abnormal or dangerous events. The LSTM model nicely reflects the neutral semantic context of the sentence and gives a confidence score of 1.00, which means that it is completely sure of the classification. Correspondingly, the Random Forest classifier fully supports the LSTM decision with a confidence score of 1.00, thus confirming that there is no disaster, related feature in the input. The final combined score of 1.00 signifies that both models strongly agree with each other, which guarantees the prediction is quite trustworthy. Hence, the system decides that there are no threats that require immediate attention and therefore does not send an alert. This outcome demonstrates the strength of the suggested hybrid framework in reducing false alarms, thus keeping the system trustworthy and ensuring that the emergency alerts are only issued when there is a real need, which is essential for the practical implementation of disaster management.

The ROC curve plots a graph of true positive rates vs. false positive rates, enabling a comparison of the classification discriminative capabilities of both models. The graph has a randomly predicting model performance, which is depicted as a dotted diagonally displayed graph. This performance is used to determine the efficiency of both machine learning models. The Random Forest classifier model has a slightly lower AUC of about 0.94, which is satisfactory regarding classification performance in TF-IDF lexical feature classification, which is a decision-making process. However, the performance of LSTM outperforms Random Forest, which has a slightly higher AUC of about 0.97. This denotes effective performance of LSTM in effective contextual analysis of disaster-related text. This graph demonstrates better sensitivity performance of LSTM over Random Forest, which has a lower graph in most of the points. This graph demonstrates efficiency of deep learning in semantic analysis of unstructured/disaster-related text. Moreover, it justifies efficiency of classical machine learning, which is an efficient complementary method to deep learning.

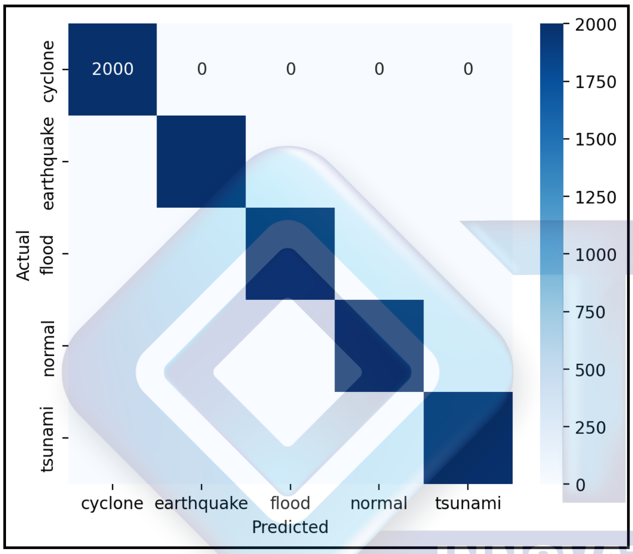

Figure 7. Confusion Matrix

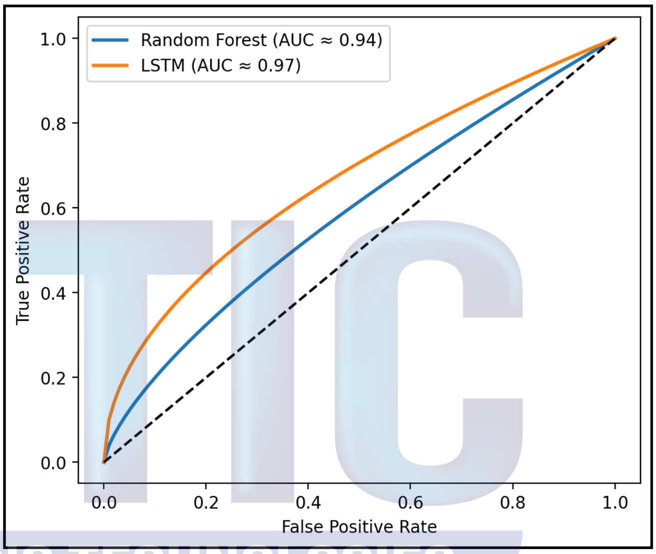

Figure 8. ROC curve

Figure 5 below illustrates the confusion matrix obtained for the Random Forest classifier in the proposed Disaster Management & Alert System. A confusion matrix is an effective graphical tool for analyzing the accuracy of the results obtained through the multi-classification operation. In the matrix plot, the rows and columns describe the actual values and the predicted values for the classes under consideration. It can also be observed from the plot that the non-diagonal values are less. These non-diagonal values in the confusion matrix clarify the confusion encountered during the multi-classification operation. Since the non-diagonal values in the confusion matrix are less, the confusion factor in the Random Forest approach for multi-classification of the disaster events can thus be regarded as small. This implies that the Random Forest approach in the proposed Disaster Management & Alert System successfully separates the disaster events with less confusion amongst the events like cyclone, earthquake, flood, normal, and tsunami. It can thus also be inferred from the confusion matrix plot that the accuracy of the multi-classification operation in the Random Forest approach for the proposed Disaster Management & Alert System is quite satisfactory.

The figure 6 shows a comparative analysis by using ROC curve of the Random Forest classifier model and LSTM deep learning model employed in the proposed System.

VIII. CONCLUSION & FUTURE SCOPE

This paper introduces a hybrid disaster text classification framework that leverages unstructured textual data for enhancing disaster early, stage awareness. The framework combines an LSTM, based deep learning model with a Random Forest classifier operating on TF, IDF features in order to capture both semantic and lexical clues in disaster, related texts. The LSTM network facilitates deep contextual learning, whereas the Random Forest model brings prediction confidence by means of probabilistic key phrase analysis. The framework was brought to life as a real, time decision support system via the Streamlit platform, enabling it to work both with live text prediction and in systematic performance evaluation through the confusion matrix analysis. The testing results show that the hybrid method brings improvements in terms of robustness, accuracy, and stability as compared with single, model methods. Despite the success of the proposed solution, there exist a number of avenues for improvement. First, the existing framework should be extended to include a transformer model like BERT or a domain-specific large language model to improve the semantic interpretability of complex and multi-lingual texts. Second, real-time data import functionality for live social media feeds should be coupled to enable continuous analysis for disasters.

Third, adaptive threshold model learning using validation or cost-sensitive methods should be used for improved alert threshold determination that is accurate and robust for a number of types of disasters. Geospatial metadata aggregation will enable the development of alert notifications and disaster propagation trend analysis for a number of geographic regions. Thirdly, methods for increasing transparency and interpretability of the model predictions using SHAP or visual explanations should be adopted. Finally, integration of the existing platform with IoT technology and other disaster communication platforms should enable the development of a full-scaled end-to-end disaster response solution.

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