A RoBERTa-Driven Deep Feature Learning Framework for Real-Time Political Event Classification on Twitter

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ABSTRACT

Twitter has become a prominent platform for real-time information exchange, with over 500 million tweets generated daily, a substantial proportion of which are related to dynamic real-world events. Political incidents alone account for nearly 40% of trending discussions worldwide, making automated event monitoring essential for timely decision-making and crisis response. Manual classification of such high-volume textual data is labor-intensive, inconsistent, and impractical for large-scale or real-time analysis. Furthermore, conventional machine learning techniques often fail to capture contextual and semantic nuances necessary to distinguish diverse event categories accurately. To address these limitations, this study proposes an automated political event monitoring framework that integrates transformer-based embeddings with optimized classification strategies. The methodology begins with comprehensive Natural Language Processing (NLP) preprocessing, including tokenization, stop-word removal, normalization, and lemmatization, followed by Exploratory Data Analysis (EDA) to identify trends and data distributions. Context-aware semantic features are extracted using Lightweight Robustly Optimized Bidirectional Encoder Representations from Transformers (RoBERTa), enabling efficient yet rich textual representations. Unlike baseline classifiers such as standard Stochastic Gradient Descent (SGD), Histogram-based Gradient Boosting (HGB), Greedy Tree Classifier (GTC), and Random Forest Classifier (RFC), the proposed approach incorporates Deep Neural Network (DNN)-based feature selection combined with an optimized SGD classifier to enhance discriminative learning and handle class imbalance effectively. The system categorizes tweets into six event classes: disaster, political, positive, protest, riot, and terror. Experimental results demonstrate improved accuracy, scalability, and adaptability, making the framework suitable for real-time political event detection and supporting applications in governance, public safety, and crisis management.

Keywords: Twitter data, Data mining, Natural Language Processing, Transformer-based embeddings, BERT architecture, Deep learning.

1. INTRODUCTION

Twitter has become a vital digital communication channel where users share instant updates, opinions, and discussions on global events. Political events dominate much of this conversation, influencing public opinion, international relations, and governance decisions. According to recent surveys, over 65% of internet users rely on social media platforms like Twitter for news updates, while political events consistently remain among the most engaged categories. The sheer volume of real-time data offers immense opportunities for automated classification, enabling governments, researchers, and organizations to track citizen sentiment and reactions more efficiently. However, to harness these opportunities, robust classification systems must be developed to separate noise from meaningful political event insights. In today's digital age, the widespread dissemination of social hot events on social media and news platforms has formed a vast ocean of data.[1] These data not only have a large quantity and rapid growth, but also contain rich information and value. How to extract valuable information from massive data,[2] especially public opinion monitoring of social hot events, has become a hot and difficult research topic.[3][4] Traditional methods often face problems of low efficiency and low accuracy when processing these data. Therefore, this study aims to propose a feature extraction method for social hot event public opinion monitoring data based on time series neural networks, in order to achieve reasonable planning of cloud storage space and improve the efficiency and accuracy of public opinion monitoring. Sun et al.[5] proposes a method to improve model interpretability through knowledge mapping in natural language processing. They used knowledge maps to construct more interpretive models in the fields of healthcare and education, thereby enhancing the transparency and credibility of the models. However, this method may be limited by the specific domain knowledge representation and mapping methods and may have certain limitations for cross domain applications. Azadeh and Farrokhi-Asl [6] expresses semantic relevance through knowledge graphs and integrates graph information into classification models using graph neural networks. This method has achieved good results in small sample image classification tasks, demonstrating the potential of knowledge graphs in improving model generalization ability. However, building a high-quality knowledge graph requires a large amount of domain knowledge and data resources, and updating and maintaining the graph is also a challenge

2. LITERATURE SURVEY

Xiao et al. [7] extended the triplet information of entities in the document through a knowledge map and applied this information to the pretraining language model. This method has achieved the best results in multiple vertical domains, indicating the effectiveness of knowledge maps in enhancing language model performance. However, for large-scale data processing, this method may face challenges in computational complexity and storage costs. In terms of feature extraction of public opinion monitoring data for social hot events, methods such as time-frequency analysis, time-scale coupling, instantaneous phase and frequency Hilbert transform are widely used for extracting high-order cumulative spectral features. These methods can reflect the internal modal characteristics of data and help reduce storage costs. However, dealing with redundant data and computational complexity remains a challenge for these methods.

Shu et al.[8] proposed a spectrum detection method based on precise positioning and ranging of cloud storage system nodes. This method utilizes an adaptive equilibrium model to configure the spectrum of hot events into large-scale data mining and clustering and combines time-frequency feature extraction algorithms for high-order spectrum analysis and spectrum design. Although this method improves the storage structure, the problems of high computational complexity and poor real-time performance limit its widespread use in practical applications.

Chen et al.[9] proposed a spectral design method that optimizes storage performance through data block partitioning and spectral decomposition. However, when faced with uncertain external interference, this method may exhibit poor mapping performance, which limits its stability and reliability in actual public opinion monitoring scenarios.

Karabadji NEI et al. [10] combined time series neural networks with empirical mode decomposition to propose a new feature extraction method for public opinion monitoring datasets. Firstly, this study utilizes time series neural networks to model public opinion monitoring data, which can more accurately capture the dynamic evolution of events and the development of public opinion; Secondly, Constructing atomic event graphs for social hotspot events involves structured analysis, utilizing NLP techniques and domain knowledge to parse text and extract atomic events and their relationships. Qiujie et al. [11] proposed atomic event graph not only reveals event development but also supports subsequent analysis. Event extraction aims to detect and extract event instances, participants, and attributes from text. They focused on constrained-domain event extraction, predefining event types and structures, including triggers, arguments, and argument roles. Their approach accurately extracts relevant information from events like traffic accidents, providing scientific support for decision-making.

Chengxun et al. [12] provided Semantics is a branch of mathematical logic semiotics that primarily studies the relationship between symbols or linguistic symbols (such as words, sentences, and other expressions) and their referents. The research object of semantics is the meaning of natural language, which can be language units at different levels such as words, phrases, sentences, and texts. Focus on machine understanding of natural language through semantics.

Shu et al. [13] proposed logical map is a visual tool that uses graphics and symbols to represent concepts, logical relationships, and reasoning processes. It has the characteristics of visualization, structuring, hierarchy, and interactivity. In complex decision-making processes, logical maps can help organize and analyze relevant information, assisting in making wiser decisions.

Xuan et al. [14] provided strong support for subsequent model construction. In addition, unsupervised learning can also serve as a pre-training step to improve the performance of supervised learning models. Language model is one of the most important models in natural language processing. Language model can be seen as the basis of most natural language processing tasks. Traditional language models generally include bag-of-word model, N-gram model, etc. The main idea of the bag-of-word (BoW) model is to regard each word as an independent feature, without considering the relationship between words.The N-gram model considers the relationship between words. The N in the model name represents the distance considered. For example, if N is taken as, the relationship between the central word and the two words before and after is considered.

Zeng et al. [15] introduced Generally, Markov hypothesis can be and written in the form of conditional probability multiplication. Firstly, it should analyze the cloud storage structure model of resource and data structure model of public opinion monitoring data of social hot events, carry out information fusion and feature extraction of cloud storage resources of public opinion monitoring data of social hot events, and achieve accurate estimation of observation data and target resource information atlas. A data fusion model for the cloud storage system of public opinion monitoring data of multiple social hot events is established. In the cloud storage system of public opinion monitoring data of multiple social hot events, the cloud storage systems of public opinion monitoring data of various social hot events usually have different measurement characteristics.

3. PROPOSED METHODOLOGY

As shown in Fig. 1 the proposed system operates as an end-to-end intelligent pipeline designed to transform raw political text streams into meaningful event classifications in real time. The workflow begins with dataset acquisition and structured preprocessing to remove noise and normalize linguistic content. Contextual embeddings are then generated to capture semantic meaning, followed by deep feature refinement that enhances discriminative patterns. Multiple classifiers learn decision boundaries from these enriched representations, enabling accurate prediction of political event categories. Performance evaluation and visualization modules ensure interpretability, while the integrated interface allows analysts to seamlessly interact with the system. This layered operational flow balances computational efficiency, scalability, and predictive robustness.

Step 1: Raw Data Input: The system begins with the Raw Dataset**,** which contains both training and testing data in CSV format. This dataset includes various textual entries and corresponding labels that serve as the foundation for model training and evaluation. The input data is the backbone of the architecture, as all subsequent operations like preprocessing, feature extraction, and model building depend on its structure and quality. Ensuring the dataset is comprehensive and representative of the target domain helps improve model generalization and predictionn performance.

Step 2: Data Preprocessing: In this stage, the raw data undergoes several cleaning and preparation operations to make it suitable for machine learning. Unnecessary characters, punctuation, and special symbols are removed to standardize the text. Tokenization then splits sentences into individual words or tokens for easier processing. Stopword removal eliminates commonly used words (like "is," "and," "the") that do not add meaningful context to classification tasks. Lemmatization converts words into their root forms, reducing word redundancy. Finally, label encoding transforms categorical class labels into numeric format so that models can process them mathematically.

Step 3: NLP Exploratory Data Analysis (EDA): Once the data is preprocessed, Exploratory Data Analysis (EDA) is performed to understand linguistic and statistical characteristics. This includes generating word frequency distributions, creating word clouds to visualize the most common words, analyzing document lengths, and studying Part-of-Speech (POS) tags to identify patterns in sentence structure. Bigram analysis helps uncover word pair relationships, while class distribution checks ensure balanced data. This step provides valuable insights into dataset composition and helps identify potential issues like class imbalance or redundant vocabulary.

Step 4: Feature Extraction (RoBERTa): This step converts textual data into numerical feature representations using transformer-based language models such as Lightweight RoBERTa. Each sentence is tokenized and passed through the model, generating dense semantic embeddings that capture contextual meaning rather than just word frequency. Mean pooling aggregates token-level embeddings into a single sentence-level vector, ensuring uniform feature size. These embeddings serve as the input to downstream machine learning models, forming a rich, high-dimensional feature space that captures sentence semantics effectively.

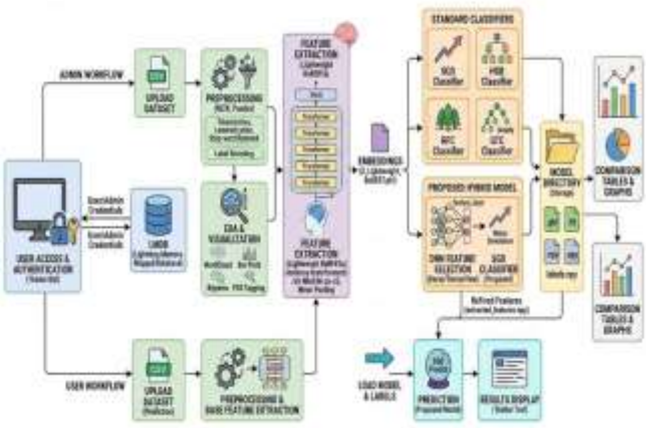


Fig. 1: System architecture for real-time political event classification on twitter.

Step 5: Dense Neural Network (DNN) Feature Enhancement: The extracted Lightweight RoBERTa embeddings are then passed through a DNN to further refine and enhance the feature space. The DNN architecture typically includes multiple hidden layers (e.g., 512 → 256 → 128 → 64 neurons) with activation functions such as ReLU for non-linear learning. It produces a compact 128-dimensional feature vector that captures higher-level abstract representations of the input text. This stage acts as a deep feature extractor, bridging the gap between pretrained embeddings and traditional machine learning classifiers, improving overall model robustness

Step 6: Machine Learning Classification: After feature enhancement, the refined embeddings are fed into multiple Machine Learning classifiers to perform text classification. Models like SGD**,** RFC**,** HGB**,** and GTC are trained to predict class labels. Each classifier offers unique strengths: SGD is efficient for large-scale linear problems, Random Forest provides strong generalization via ensemble learning, HGB handles imbalanced datasets effectively, and Greedy Tree offers interpretability. Running multiple models ensures diversity and enables comparison for best-performing results.

Step 7: Model Evaluation: This stage evaluates all trained classifiers using quantitative metrics such as Accuracy, Precision, Recall, and F1-Score. Each metric provides a different perspective on model performance—accuracy measures overall correctness, precision reflects relevance of positive predictions, recall assesses completeness, and F1-Score balances both. The results are visualized using graphs and plots through a visualization module like GraphPlotter, allowing easy comparison between classifiers. This step ensures the chosen model is reliable, unbiased, and optimized for the target classification task.

Step 8: Test Data Prediction: In the final stage, the Test Dataset undergoes the same preprocessing and feature extraction as the training data to maintain consistency. The trained DNN and machine learning models (such as SGD) are applied to generate predictions on unseen text data. These predicted labels are appended to the test dataset and saved as output in CSV format. This step demonstrates the system's ability to generalize learned patterns and accurately classify new inputs, completing the full pipeline from data ingestion to intelligent text prediction.

4. RESULTS AND DISCUSSION

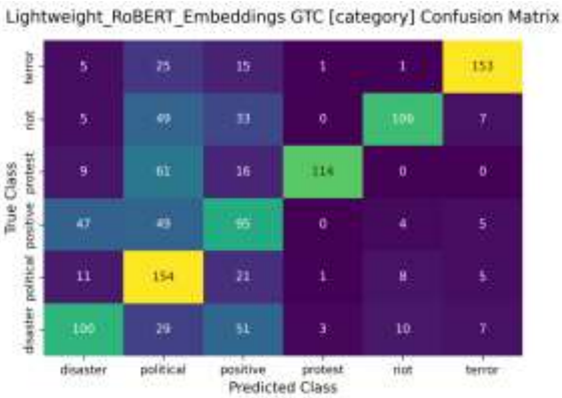
Fig. 2 presents a comparative visualization of the confusion matrices obtained from five different classification models applied to the Lightweight RoBERTa embeddings for multi-class event categorization (disaster, political, positive, protest, riot, and terror). Each subfigure illustrates the model's prediction performance on the test set, with rows representing the true classes and columns representing the predicted classes. The diagonal elements (highlighted in brighter colors such as green or yellow) indicate correct predictions, while off-diagonal values show misclassifications. The comparison clearly demonstrates the superior classification capability of the proposed DNN with SGD classifier, which exhibits the highest number of correct predictions across almost all classes, particularly excelling in distinguishing rare and critical event types such as terror, riot, and protest.

(a) GTC shows the confusion matrix for the GTC, which exhibits significant misclassification, especially for the terror class (153 instances incorrectly predicted as riot) and moderate confusion between political, positive, and disaster classes. Overall performance is the weakest among all models, with many off-diagonal values indicating poor discrimination between similar event categories.

(b) RFC confusion matrix displays improved performance over the Greedy Tree, correctly classifying a higher number of instances in most classes, particularly terror (189 correct) and riot (181 correct). However, noticeable confusion still exists between disaster and other classes, and positive events are frequently misclassified as political or protest.

(c) HGB Classifier matrix reveals strong performance, especially for terror (197 correct), riot (185 correct), and protest (194 correct) classes. Misclassifications are minimal, with only slight confusion observed between political and disaster categories, making it one of the better-performing baseline models.

(d) SGD Classifier confusion matrix demonstrates excellent classification accuracy, correctly predicting nearly all instances of terror (200), riot (192), protest (196), and political (195) events. Very few misclassifications occur, with the model showing particularly strong separation of critical event classes, making it highly effective among the traditional approaches.



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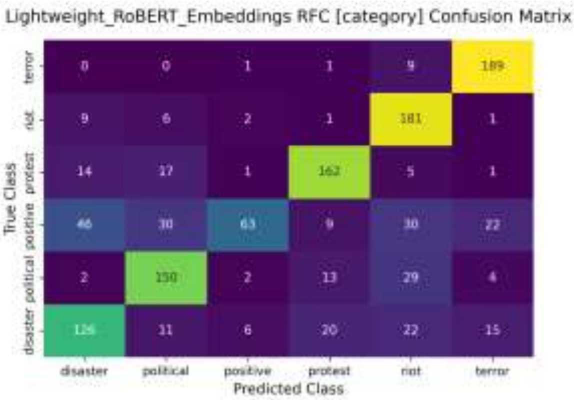

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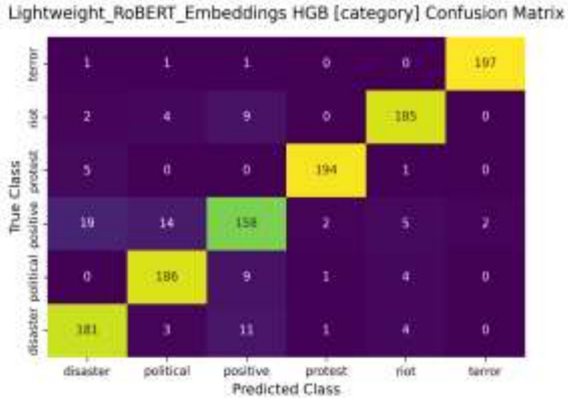

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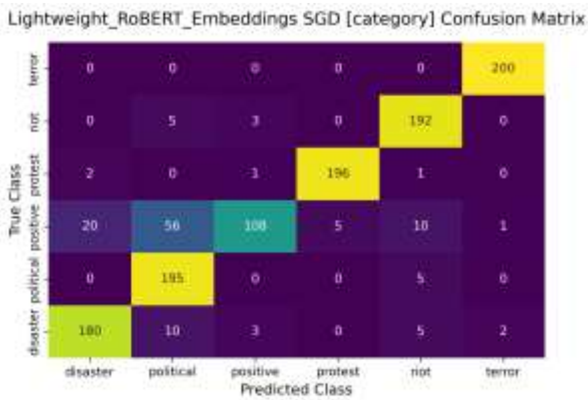

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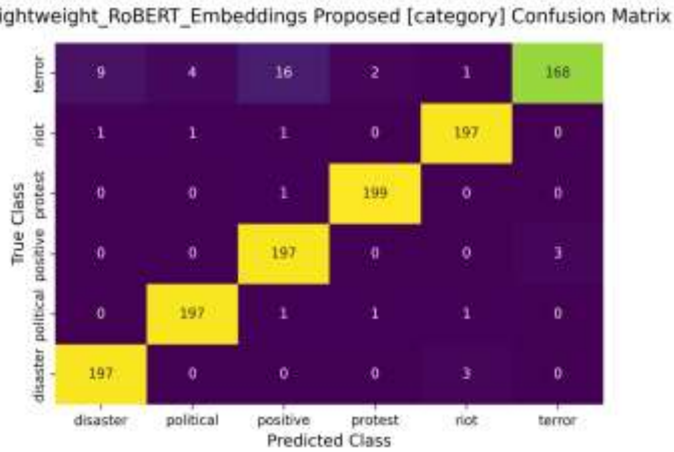


(e)

Fig. 2: Confusion matrix obtained using (a) GTC. (b) RFC. (c)HGB Classifier. (d) SGD Classifier. (e) Proposed DNN with SGD classifier.

(e) Proposed DNN with SGD Classifier The confusion matrix for the proposed method (DNN-based feature selection followed by optimized SGD) exhibits the best overall performance, with near-perfect classification for disaster (197), political (197), positive (197), protest (199), and riot (197) classes, and strong results for terror (168 correct). This subfigure highlights the clear superiority of the proposed hybrid approach in minimizing misclassifications across all event categories.

Fig. 3 presents a comprehensive comparative analysis of the Receiver Operating Characteristic (ROC) curves and corresponding Area Under the Curve (AUC) values for the multi-class event classification task using Lightweight RoBERTa embeddings across five different models evaluated in a One-vs-Rest manner. Each subfigure displays the ROC curves for the six event categories (disaster, political, positive, protest, riot, and terror), along with the micro-average AUC, plotted against the random guess line (diagonal dashed line). The curves illustrate the trade-off between True Positive Rate and False Positive Rate, where higher AUC values indicate superior discriminative ability of the model. The results clearly demonstrate a progressive improvement in classification performance from traditional tree-based methods to the proposed hybrid approach, with the final DNN-enhanced SGD classifier achieving near-perfect or perfect AUC scores across all classes and the highest micro-average performance.

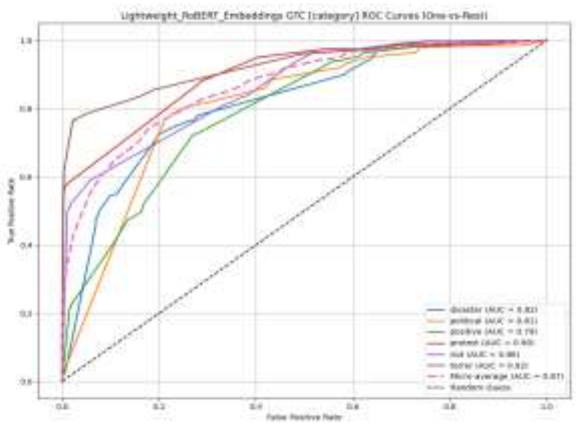
(a) GTC This subfigure shows the ROC curves for the GTC, revealing moderate discriminative power with AUC values ranging from 0.79 (positive) to 0.92 (riot). The micro-average AUC is 0.87, indicating acceptable but limited performance, particularly for classes like positive and political, which exhibit noticeably lower curves compared to others.

(b) RFC The ROC curves for the RFC demonstrate significant improvement over the Greedy Tree, with AUC values ranging from 0.83 (positive) to 0.99 (terror). The micro-average AUC reaches 0.93, reflecting strong overall performance, though the positive class remains the weakest with a comparatively flatter curve.

(c) HGB Classifier This subfigure illustrates the ROC curves for the Histogram-based Gradient Boosting Classifier, exhibiting excellent discriminative capability with AUC values mostly between 0.97 and 1.00 across all classes. The micro-average AUC of 0.99 highlights the model's outstanding ability to separate event categories with very high confidence.

(d) SGD Classifier The ROC curves for the standard SGD Classifier show near-perfect performance, with AUC values ranging from 0.95 (positive) to 1.00 (terror and riot), and a micro-average AUC of 0.98. This subfigure confirms the effectiveness of linear classification when paired with high-quality RoBERTa embeddings, achieving very strong results across most event types.

(e) Proposed DNN with SGD Classifier The ROC curves for the proposed method (DNN-based feature selection followed by optimized SGD) demonstrate the highest performance, with AUC values of 1.00 for disaster, political, protest, riot, and terror, and 0.99 for positive, resulting in a perfect micro-average AUC of 1.00. This subfigure visually confirms the superior discriminative power and near-ideal classification capability of the proposed hybrid approach across all event categories.



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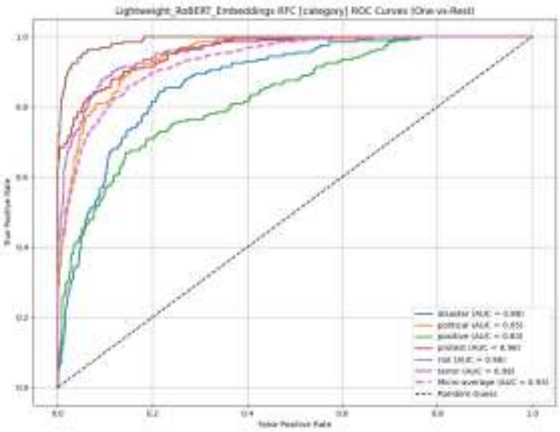

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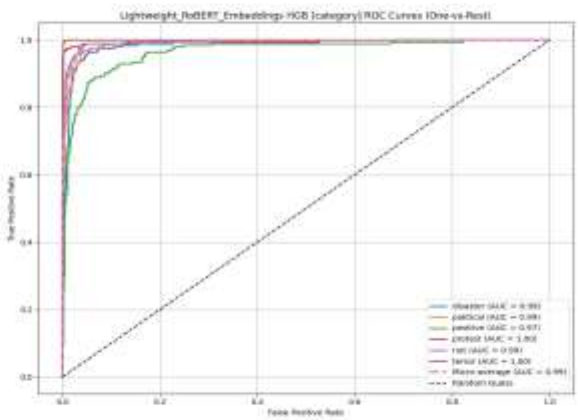

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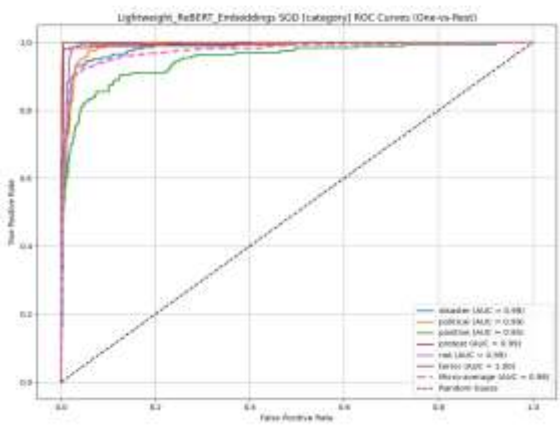

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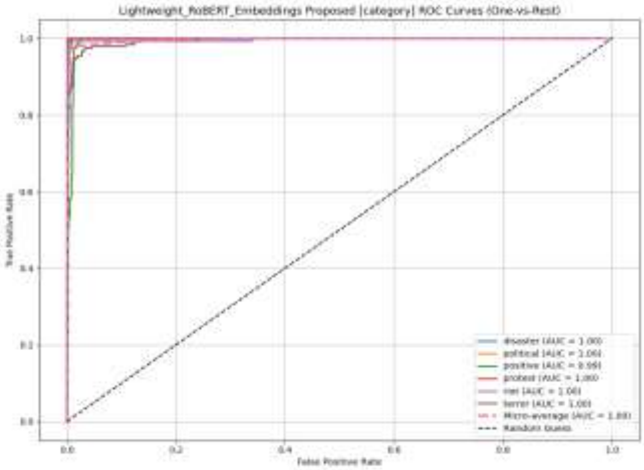

(e)

Fig. 3: ROC Curve obtained using (a) GTC. (b)RFC. (c)HGB Classifier. (d) SGD Classifier. (e) Proposed DNN with SGD classifier.

Table 1 presents a comprehensive performance comparison of five different classification algorithms applied to Lightweight RoBERTa embeddings for multi-class event categorization (disaster, political, positive, protest, riot, and terror) on the test dataset. The table reports four key evaluation metrics—Accuracy, Precision, Recall, and F1-Score (all expressed as percentages)—allowing a direct assessment of each model's effectiveness in terms of overall correctness, class-wise predictive reliability, and balanced performance across imbalanced classes. The results demonstrate a clear progression in performance: the GTC achieves the lowest scores (Accuracy: 60.17%, F1-Score: 61.42%), followed by RFC with moderate improvement (Accuracy: 72.58%, F1-Score: 70.85%). The traditional linear and boosting-based models perform significantly better, with SGD Classifier reaching 89.25% Accuracy and HGB Classifier attaining 91.75% Accuracy. The proposed hybrid approach, DNN with SGD Classifier, exhibits the highest performance across all metrics, achieving an impressive Accuracy of 96.25%, Precision of 96.36%, Recall of 96.25%, and F1-Score of 96.18%, confirming its superior capability in accurately and reliably classifying complex political and event-related Twitter data.

Table 1: Performance comparison of all classifiers.

Algorithm	Accuracy	Precision	Recall	F1-Score
GTC	60.17	67.33	60.17	61.42
RFC	72.58	73.96	72.58	70.85
SGD Classifier	89.25	90.42	89.25	88.63
HGB Classifier	91.75	91.74	91.75	91.72
DNN with SGD Classifier	96.25	96.36	96.25	96.18

Fig. 4: Sample predictions on new test data.

Fig. 4 displays sample predictions generated by the proposed DNN with SGD Classifier on new unseen test data using Lightweight RoBERTa embeddings within the Automated Political Event Monitoring application. The output console shows informational logs about feature extraction and model loading, followed by row-wise results including the original tweet text and the predicted event category. Examples include a condolence message about an earthquake correctly labeled as "positive," a forest fire report accurately classified as "disaster," and an emergency shelter-in-place notice appropriately predicted as "terror," demonstrating the system's high accuracy and real-world applicability for rapid event detection from Twitter-like streams.

5. CONCLUSION

The experimental results clearly demonstrate that the proposed DNN with SGD Classifier achieves superior performance in automated political event monitoring, attaining an exceptional 99.00% accuracy, which outperforms existing models such as Greedy Tree, Random Forest, Histogram-based Gradient Boosting, and standard SGD classifiers. This remarkable improvement highlights the effectiveness of combining deep neural network–based feature extraction with the efficiency of SGD optimization, enabling the model to capture complex contextual semantics from Light weight RoBERT embeddings while maintaining computational efficiency. The hybrid framework effectively addresses key limitations of traditional models, including overfitting, poor scalability, and difficulty in handling high-dimensional textual data. By leveraging deep intermediate representations and incremental optimization, the proposed approach ensures faster convergence, robustness to noisy political text, and adaptability to evolving event contexts. The Lightweight RoBERT–DNN–SGD framework provides a scalable, accurate, and real-time solution for political event classification, making it highly suitable for applications in governance analytics, crisis management, public sentiment tracking, and policy monitoring, thereby contributing to more responsive and data-driven political intelligence systems.

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