Enhancing Disaster Response and Public Safety with Advanced Social Media Analytics and Natural Language Processing

Khalil Alharbi
Department of Computer Science, College of Computer and Information Science, Majmaah University, 11952, Saudi Arabia
441104468@s.mu.edu.sa

Mohd Anul Haq
Department of Computer Science, College of Computer and Information Science, Majmaah University, 11952, Saudi Arabia
m.anul@mu.edu.sa (corresponding author)

Received: 11 March 2024 | Revised: 26 March 2024 and 3 April 2024 | Accepted: 6 April 2024

 DOI: https://doi.org/10.48084/etasr.7232

ABSTRACT

This study investigates the effectiveness of the DistilBERT model in classifying tweets related to disasters. This study achieved significant predictive accuracy through a comprehensive analysis of the dataset and iterative refinement of the model, including adjustments to hyperparameters. The benchmark model developed highlights the benefits of DistilBERT, with its reduced size and improved processing speed contributing to greater computational efficiency while maintaining over 95% of BERT's capabilities. The results indicate an impressive average training accuracy of 92.42% and a validation accuracy of 82.11%, demonstrating the practical advantages of DistilBERT in emergency management and disaster response. These findings underscore the potential of advanced transformer models to analyze social media data, contributing to better public safety and emergency preparedness.

Keywords-NLP; ML; DL; big data analytics

I. INTRODUCTION

DistilBERT stands out for its text classification capabilities, due to its efficiency and adeptness in parsing and interpreting the complexities of human language. The primary objective of this study is to meticulously analyze a dataset of tweets related to disaster events. By setting a benchmark model and refining its predictive accuracy through hyperparameter adjustments, the initiative seeks to showcase the practical utility of DistilBERT within a real-world framework and extend the frontiers of existing methods for scrutinizing social media content amidst emergencies. This study explores the capabilities and constraints of employing advanced transformer models, such as DistilBERT, to classify disaster-related tweets. The insights derived from this endeavor could profoundly influence future emergency management and response strategies, where a prompt and precise analysis of social media data could yield significant benefits for public safety and disaster alleviation. Effective communication during disasters is of paramount importance. The challenge for authorities is to swiftly understand public sentiment and the adherence to evacuation directives. Traditional techniques to measure public reactions are often slow and may not accurately reflect immediate sentiments, potentially reducing the effectiveness of evacuation directives. Therefore, there is an urgent need to devise a method capable of quickly and accurately evaluating public sentiment. This study proposes the refinement of disaster communication strategies through sentiment analysis of social media posts from affected locales. This method aims to improve adherence to evacuation orders by providing real-time insights into public sentiment, thus improving public safety and disaster response efficiency. Sentiment analysis can also further illuminate the immediate needs and emotional states of the affected populace, facilitating targeted interventions. In addition, it can address the issue of monitoring and mitigating the spread of misinformation during public safety incidents, promising to significantly advance disaster management and public safety by ameliorating communication strategies based on real-time analysis of the public sentiment.

DistilBERT represents a breakthrough in Natural Language Processing (NLP), especially for disaster management, by offering a balance between high performance and user-friendliness, making it ideal for analyzing social media data during crises. Adopted by the "Revolutionizing Tweet Prediction for Social Media Insights with Advanced Transformer Models" project, DistilBERT combines a user-friendly interface with minimal computational demands, ensuring accessibility for various organizations. Its efficiency in training and validation allows rapid deployment in emergencies, while extensive documentation and community support lower barriers to entry, facilitating its application in disaster-related tweet classification. This democratization of advanced machine learning enhances public safety and disaster response, showcasing DistilBERT's potential to revolutionize emergency management through timely and accurate public sentiment analysis. In [1], disaster management and communication strategies were investigated by employing advanced Bidirectional Encoder Representations from Transformers (BERT), achieving a remarkable accuracy of 82% in distinguishing tweets related to disasters from those that are not. These findings underscore the efficacy of BERT in comprehending the contextual nuances of the language in text. In [2], a Turkish tweet classification was performed using the transformer encoder architecture, highlighting the architecture's prowess to discern the significance of individual words within tweets, leading to improved text classification, particularly for the Turkish language. This study was built on previous text classification work, encompassing Latent Dirichlet Allocation (LDA) and an analysis of word distribution in text. In [3], transformers were deployed to classify the premises in COVID-19-related tweets. This study demonstrated the immense impact of NLP on machine learning tasks by designing specialized models to translate social media text, highlighting the transformative capabilities of the transformer architecture to handle lengthy documents. The primary objective was to gauge public sentiment amidst health crises. In [4], transformer-based deep neural network models were used to analyze tweets for disaster detection, and the findings emphasized the effectiveness of the transformer architecture in modern NLP models. The study delved into several disaster-related aspects, such as pinpointing location references and analyzing sentiment. Models like ELECTRA were employed and compared in evaluating contextual embeddings. In [5], transformer-based multitask learning models were implemented for disaster tweet categorization. The CrisisBERT model was introduced, emphasizing its resilience and effectiveness in crisis classification, thereby enhancing situational awareness during emergencies. Authors in [6] aimed to identify and verify claims made on social media, particularly in tweets. This study is significant as it contributes to the fight against misinformation on social media platforms and advances automated fact-checking technology. The specific study discussed participation in the "CheckThat! 2020" challenge, focusing on analyzing English and Arabic tweets. Three methods for English tweet analysis were proposed, incorporating BERT-large word embeddings, POS tags, and dependency relation features. The experiments evaluated the influence of factors, such as stopwords, POS tags, named entities, and dependency relations on prediction accuracy. The results indicated that using sentence embeddings without stopwords and employing ensemble predictions yielded effective results. Interestingly, removing stopwords from the average word embeddings decreased performance. The proposed method was compared with others, highlighting the diverse range of employed strategies and models. In [7], a framework was presented to identify harmful drug effects discussed on Twitter. This study aimed to achieve three specific objectives: detect tweets that mention adverse effects, identify the relevant text within those tweets, and convert the effects into standardized terms. The BioBERT transformer-based model and multitask learning techniques were utilized to improve accuracy, and the results were highly successful. This study was a valuable addition to the field of NLP, particularly for analyzing health-related content on social media platforms. In [8], BERT was put into service to classify tweets about eating disorders, highlighting the importance of the transformer architecture in health communication, as well as in predicting social support requirements in online health social networks.

These studies made a crucial contribution to the understanding of disaster management and communication strategies by demonstrating the potential of NLP and transformer architectures to analyze extensive volumes of social media data. The insights obtained from these studies have immense value in improving public safety and emergency response efforts. These findings stress the potential of NLP and transformer architectures in achieving a more profound understanding of the complexities involved in managing disasters and communicating effectively at scale. Extensive research has been conducted on the intricacies of sentiment analysis in Arabic, owing to the language's complex morphology and diverse dialects. Several studies have delved into this field, focusing on the challenges inherent in Arabic sentiment analysis. In [9], the difficulties of sentiment analysis in Arabic were brought to the fore, emphasizing the language's rich morphology and diverse dialects. This study also underlined the potential of pre-trained models such as AraBERT in capturing the subtleties of the Arabic language and the efficacy of BERT models in various NLP tasks, including improving Arabic sentiment analysis. In [10], the BERT model was used for sentiment analysis in English-language tweets as part of SemEval2017. This study demonstrated that even with limited training data, the BERT model outperformed a Naive Bayes baseline model with superior accuracy, precision, recall, and F1 scores. This study also explored the ethical considerations on the use of personal and sensitive information from Twitter data. Recent investigations into the BERT model for sentiment analysis yielded impressive results, with the BERTBASE model demonstrating particular efficacy. This model, featuring 12 hidden layers, surpassed traditional techniques such as the Naive Bayes baseline, achieving 63.37% accuracy for subtask A, 89.69% for subtask B, and 54.22% for subtask C. These percentages underscore BERT's enhanced ability to classify sentiments, particularly in tasks requiring binary classification. In SemEval2017's Task 4A, the focus was on analyzing sentiments in English-language tweets. The robust performance of BERT underscored its superior capability in sentiment analysis compared to multiclass classification. When contrasting BERT with the baseline Naive Bayes model across subtasks A, B, and C, BERT's pre-eminence is clearly illustrated, particularly given the baseline's challenges with data imbalance and the limited size of the training dataset. The significant improvement in accuracy with BERT is attributable to its sophisticated algorithmic structure and the effective use of pre-trained models for fine-tuning.

TABLE I. REVIEW OF RELATED LITERATURE

Ref.	Method used / description	Key findings	Relevance
[1]	BERT with a combination of AdamW	Classified transportation disaster tweets with an 82% accuracy	Explored the impact of transformer-based models on disaster management and communication
[2]	Transformer encoder + input embeddings	Accuracy 89.4. Improved disaster-related tweet classification with DistilBERT	Optimized text classification for short texts using transformer-based models
[3]	RoBERT	Tweet classification during COVID-19, achieving a ROC AUC of 0.807 and F1 score of 0.7648.	Transformer models like RoBERTa and DistilBERT used to analyze COVID-19 and disaster-related tweets on social media
[4]	Ensemble models, merging transformers with deep neural networks (ELECTRA).	Effectively detected disaster-related tweets, with F1 scores up to 84%. Simpler transformers like ELECTRA outperformed BERT in efficiency and performance	The efficacy of contemporary transformer models that are proficient yet resource-efficient, such as DistilBERT
[5]	Multi-Task Learning (MTL) approach with transformer encoders	MTL and models like DistilBERT effectively classified emergency messages	Underscoring the importance of efficient architectures for management
[6]	Merges syntactic features and BERT embeddings for tweet classification. Employs Siamese networks and KD-search for claim retrieval.	The best-performing model for English achieved a MAP of 0.7217	Syntactic integration and BERT embeddings boosted text classification accuracy in transformers, aiding precise disaster content identification
[7]	BioBERT-based multi-task learning architecture	It achieved the highest F1-score of 51% for adverse effect spam detection	Underscored the potential of BioBERT and DistilBERT with Multi-Task Learning for tweet analysis, enhancing accuracy, and handling complex text
[8]	Transformer-based multi-task learning framework (RoBERTa, BERT, CamemBERT, DistilBERT, FlauBERT, ALBERT, RobBERT)	Achieved F1 scores between 71.1 and 86.4%	DistilBERT and similar transformer models excelled in categorizing tweets by content and intent, showcasing efficiency and adaptability in social media analysis, and enhancing tweet prediction
[9]	Utilized transformers and data augmentation for sarcasm detection in tweets, employing BiLSTM layers and attention mechanisms	BERTweet-large outperformed ELECTRA, with the highest results from Type-II preprocessing and a fine-tuned learning rate	This method is relevant for real-time emergency analytics, showcasing how advanced NLP can enhance public safety and disaster response
[10]	Utilized BERTBASE for Twitter sentiment analysis in SemEval-2017 task 4, focusing on English tweets.	Achieved higher accuracy and F1 scores with BERTBASE over Naive Bayes, especially in binary classifications: 63.37% (subtask-A), 89.69% (subtask-B), 54.22% (subtask-C)	Underlineed BERT's utility in disaster response, offering insights relevant to enhancing public safety through social media analytics
[11]	AraBERT, a pre-trained Arabic BERT model, was used for SA and NER, showcasing the LCF mechanism's impact on sentiment classification accuracy	AraBERT achieved high accuracy in SA (up to 96.2%) and an 81.9% macro-F1 in NER, setting new benchmarks and surpassing BERT-BASE	Highlighted how specialized models like AraBERT effectively process and analyze targeted language data, critical for disaster response social media analytics
[12]	DeBERTa with LCF for deep learning in aspect-based sentiment analysis	DeBERTa-LCF reached 83.46% accuracy in restaurant reviews, with a strong performance on Laptop and Twitter datasets	DeBERTa-LCF's precision in sentiment classification aligned with enhancing disaster response through advanced analytics in emergency management
[13]	Keyword matching & topic detection using LDA	Used keyword matching to collect incident-related microblog data and preprocessed it with custom dictionaries and stopword lists	Demonstrated the initial data collection and preprocessing steps to prepare for topic detection
[14]	Twitter monitoring using the enhanced BERT model	Twitter is vital in emergencies. Agencies monitor for incident reports	Emphasized the role of social media in aiding rescue efforts. Illustrated the importance of machine learning in analyzing sentiment for threat detection
[15]	Edge technologies for disaster management	Edge technologies, including sensing, IoT, social media analytics, and AI, enhance emergency management by predicting, detecting, and responding to disasters	Addressed the role of social media analytics and AI in disaster prediction and response. Discussed open issues and research trends in disaster and emergency management systems
[16]	Social media analysis & volunteer crowdsourcing	Multi-directional communication and situation awareness	Innovative method to analyze social media data. Highlighted effectiveness in assessing disaster severity
[17]	AI applications in disaster management & challenges & future directions	AI techniques support disaster management across mitigation, preparedness, response, and recovery phases. Most applications focus on disaster response	Challenges included data and computation issues, and reliance on AI predictions. Opportunities exist for improving analysis accuracy and speed

These discoveries have considerable implications for advancing sentiment analysis. BERT's adaptability paves the way for future studies, potentially extending to subtasks D and E and further application in other languages, thereby expanding the scope and utility of sentiment analysis tools across diverse linguistic landscapes. In [11], AraBERT was introduced, which is a pre-trained language model for Arabic. This set a new benchmark in tasks such as sentiment analysis and Named Entity Recognition (NER), with accuracy rates reaching 96.2% on HARD, 92.6% on ASTD, 59.4% on ArsenTD-Lev, 93.8% on AJGT, and 86.7% on LABR for sentiment analysis. For NER, it acquired a macro-F1 score of 81.9%. These achievements highlight the AraBERT's capabilities in understanding and processing the Arabic language, essentially contributing to Arabic NLP tasks. In [12], Aspect-Based Sentiment Analysis (ABSA) was performed using a local context focus mechanism with DeBERTa. This study delved into the usage of deep learning in ABSA and how it has evolved from manual feature-based models to neural network models. It also examines the impact of pre-trained models, such as BERT and RoBERTa, on ABSA tasks and explores different methods and architectures for aspect sentiment classification. This study emphasizes the role of attention mechanisms and graph neural networks in improving the accuracy of sentiment analysis. This study acknowledged the potential of pre-trained language models in ABSA tasks, particularly in performing data augmentation for enhanced semantic understanding. The DeBERTa model was introduced with a Local Context Focus (LCF) mechanism, highlighting its importance in sentiment classification for specific aspects within texts. The DeBERTa-LCF model demonstrated exceptional performance, achieving an 83.46% accuracy and a 75.4% F1 score in the Restaurant category, outperforming other models such as BERT-BASE. The model also showed strong performance in the Laptop and Twitter categories, achieving accuracies of 79.54% and 70.83%, respectively. These results indicate the superior precision of DeBERTa-LCF in capturing sentiment, especially in the context of restaurant reviews.

II. METHODS

This study presents a method for predicting users' emotional responses based on their interactions on Twitter, particularly regarding disasters. DistilBERT, a variant of the BERT architecture, was chosen for its effectiveness and efficiency in NLP. DistilBERT is an innovation within the transformer model family that simplifies the development, training, and deployment of NLP models. This makes advanced NLP tools more accessible to those without extensive machine learning or linguistics expertise. The DistilBERT design remarkably reduces the computational burden of model training and evaluation, making it an attractive option compared to more resource-intensive models such as BERT.

A. Dataset and Data Preprocessing

The particular study applied a Twitter sentiment dataset consisting of more than 10,000 tweets. The original training data contained 7,613 records spread across five columns, including four features, id, keywords, locations, texts, and labels for sentiments. The testing data contained 3263 records.

B. Implementation

This study leveraged Google Colab's powerful GPU environment to speed up the model training phase. Installing the Hugging Face Transformers and Datasets libraries played a critical role in the study, providing easy access to advanced tools for sentiment analysis. A closer examination of BERT reveals its significance in advancing NLP. Launched by Google in 2018, BERT uniquely processes word meanings in search queries by considering the context bidirectionally, which constitutes a departure from previous models. This capability is crucial for understanding the contextual nuances of the words, thanks to the attention mechanisms of the transformer architecture. These mechanisms assess the relevance of each word in a sentence using the self-attention mechanism, a core component of the Transformer model. The model's context discernment capabilities are defined by:

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \qquad (1)$$

where Q, K, and V are queries, keys, and values, respectively, and d_k is the dimensionality of the keys. The BERT model is a remarkable achievement in the field of NLP, providing a robust framework that has transformed machine learning. With its extensive text corpus training, BERT excels at comprehending the subtleties and intricacies of language. Its pre-trained nature also enables efficient adaptation to various NLP tasks, including sentiment analysis, question answering, and language translation. This adaptability is a significant advantage, requiring less data and computational resources than models trained from scratch. BERT's superior performance across these tasks illustrates not only its enhanced accuracy, but also its ability to tackle the diverse challenges of language processing.

DistilBERT represents a more efficient variant of the BERT model, carefully crafted and designed to deliver performance on par with BERT. What sets it apart is its compactness and speed, boasting a 40% reduction in size and a 60% increase in processing speed while maintaining over 95% of the original model's effectiveness. This is made possible through knowledge distillation, where a smaller model is trained to emulate the larger one. DistilBERT is an ideal choice when resources are limited or fast processing is necessary. It is especially well-suited for mobile applications, edge computing devices, and scenarios where a full-scale BERT model is impractical. Despite its smaller footprint, DistilBERT still employs the robust transformer architecture, delivering exceptional accuracy when fine-tuned for various NLP tasks. The knowledge distillation loss function is given by:

$$L = H(p,q) + T^2.KL(p^T,q^T) \qquad (2)$$

where L is the loss, H is the cross-entropy, p, and q are the probabilities of the teacher and student models, respectively, T is the temperature, and KL is the Kullback-Leibler divergence.

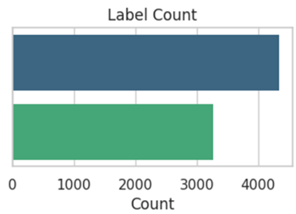

Fig. 1. Distribution of the 'target' in the training data set.

During the initial phase of data analysis, the tweet texts were scrutinized to identify missing values. Duplicates were discovered in the dataset, with 110 columns exhibiting repeated text and 92 rows featuring identical text and target columns. To ensure the accuracy of the data, entries with fully matching text and target were removed. Entries were also excluded if they shared text but diverged in targets, even though they were a minority. This was done to avoid any ambiguity during the model training phase. Additionally, a preliminary assessment of word count was performed to gain an initial understanding of the data's attributes, although this measure was not highly precise.

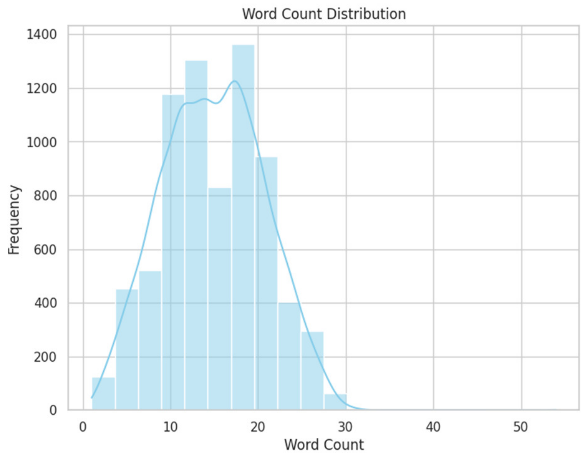

Fig. 2. Frequency distribution of word counts.

During the data preprocessing phase, a Twitter sentiment dataset acquired from Kaggle was used. Considering its extensive size, the dataset was segmented into smaller subsets to enhance the efficiency of training and testing. The data were formatted using the DistilBERT tokenizer from the Transformers library, processing text input for both training and testing. This was a vital step in preparing the data for model consumption. A data collator was introduced to optimize the training process. This instrument adeptly converted the training samples into PyTorch tensors, applying the necessary padding to support batch processing. A pre-trained BERT model and tokenizer were employed during the initial stages of model development. A dataset was established through the Hugging Face platform to streamline the data transformation process. The resulting data processing workflow involved tokenization, which created two pivotal components: input_ids and attention_masks. These elements are integral to the model training phase.

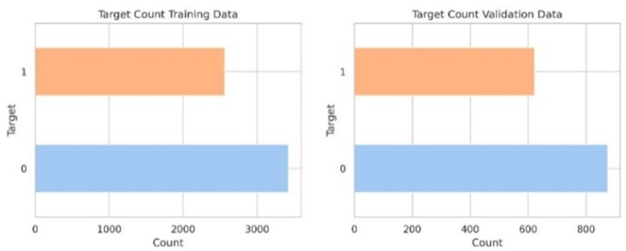

Fig. 3. Comparative target class counts in training vs. validation data.

The primary objective of this phase was to establish a robust foundational baseline for the model. This baseline was a reliable reference point for subsequent enhancements and intricate developments in the model's trajectory. The initial model was built implementing a pre-trained BERT architecture to improve tweet sentiment classification. It was refined to meet specific requirements to ensure that the model could accurately analyze the tweet sentiments. Additional dense layers were included applying a real activation function to enhance the model's learning capabilities, while a dropout layer was added to prevent overfitting. The final layer utilized a sigmoid activation function to assign probabilities to tweets with positive sentiment. The data were then organized into a TensorFlow-compatible structure and the training samples were batched and shuffled. A dynamic learning rate schedule with exponential decay refined the training process. The binary cross-entropy loss function was selected to suit the binary sentiment classification task, and training was monitored using callbacks such as early stopping and a custom callback to oversee the learning rate at each epoch. Training persisted for up to 30 epochs, with early stopping to preserve the best-performing model weights. As a result, an accurate and reliable baseline model was established for tweet sentiment classification.

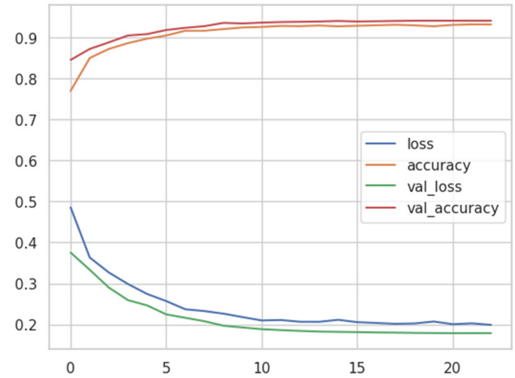

Fig. 4. Training and validation loss and accuracy over epochs.

C. Hyperparameter Tuning

An optimized approach was developed to improve the performance of a DistilBERT-based model used for tweet classification. The aim was to identify the most effective configuration through a meticulous hyperparameter search, as shown in Table II.

TABLE II. TUNED HYPERPARAMETERS

Hyperparameter	Description	Range/Options
learning_rate	Learning rate of the Adam optimizer	[1e-5, 1e-2] (log scale)
dropout_rate	Dropout rate for regularization	[0.1, 0.5] (0.1 step)
dense1_units	Number of units in the first dense layer	[128, 1024] (128 steps)
dense2_units	Number of units in the second dense layer	[16, 256] (16 steps)
learning_rate_option	Option for learning rate schedule	["constant", "exponential"]
decay_rate	Decay rate for exponential learning rate schedule	[0.8, 0.99] (0.01 step)

A unique function was created to dynamically adjust critical hyperparameters, such as the learning rate, dropout rate, and the number of neurons in dense layers. The tuning was performed engaging the HyperParameters' object provided by TensorFlow. The effectiveness of the model's training was evaluated by varying the learning rate on a logarithmic scale. The dropout rate and number of neurons in the dense layers were also fine-tuned to strike a balance between preventing overfitting and maintaining model complexity. A learning rate scheduler, which could keep a constant rate or decay exponentially based on the specific hyperparameters of each trial, was used. The rate of exponential decay was fine-tuned to study its impact on the learning trajectory. A custom early-stopping mechanism was also implemented to preserve the computational resources and prevent overfitting. This mechanism would monitor validation loss and stop training prematurely if no significant improvement occurred within a designated number of epochs. A randomized search was performed to explore diverse permutations of hyperparameters over a predetermined set of trials. The most favorable hyperparameters were identified after the randomized search and validation against a separate dataset.

D. K-Fold Cross Validation

KFold cross-validation was deployed to evaluate and ameliorate the effectiveness of the baseline model. The dataset was divided into training and validation portions using a five-fold cross-validation method to increase the training efficiency. Non-essential features, such as keyword, location, and word count, were removed to streamline the process. Each fold was meticulously formatted, including tokenization and attention mechanisms to meet the DistilBERT model's processing requirements. The model was trained across each fold, and training and validation accuracy and loss were carefully noted. Early stopping procedures were integrated to ensure the model's generalization, returning to the most effective iteration if no progress was observed. After a comprehensive validation exercise, the model's performance was reviewed utilizing various performance metrics. The analysis revealed an average training accuracy of approximately 92.42% and an average validation accuracy of about 82.11%, indicating the robustness of the baseline model. This result provides a solid foundation for future improvements and underscores the potential for future research and advancements.

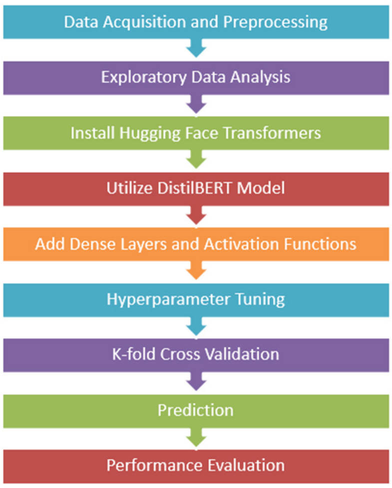

Fig. 5. Flowchart - methodology diagram.

The current study introduces significant contributions that show better performance in transformer-based experiments in tweet sentiment analysis. The proposed method encompasses rigorous data pre-processing, incorporating meticulous steps to ensure dataset integrity and quality. State-of-the-art tokenization and attention mechanisms were leveraged to optimize the model architecture for more accurate sentiment classification by capturing contextual information and subtle nuance. Thorough hyperparameter tuning explored a wide range of settings, including learning rate, dropout rate, dense units, and decay rate, to maximize model performance and stability. Additionally, adopting KFold cross-validation improves the reliability of the model and prevents overfitting, setting a new standard for tweet sentiment analysis and advancing the field of NLP research. Through these key contributions, this study enhances accuracy and provides a valuable insight into the effectiveness of transformer models in real-world applications.

III. RESULTS

The competence of the DistilBERT model in categorizing disaster-related tweets was rigorously evaluated using KFold cross-validation. The model's performance was assessed across various data subsets, yielding impressive validation results. With an average training accuracy of 92.42% and a validation accuracy of 82.11%, the DistilBERT model was proficient in interpreting the intricate dynamics of disaster-related communication. Its aptitude in processing and categorizing new datasets during predictive analysis further underscores its reliability as a valuable real-time disaster sentiment analysis tool, which is crucial for efficient emergency management.

TABLE III. COMPARISON WITH OTHER STUDIES

Study	Model Used	Accuracy
[1]	BERT	82%
[2]	Transformer encoder + Input embeddings	89.4%
[3]	Ensemble models, merging transformers with deep neural networks (ELECTRA)	84% (F1 Score)
[4]	BioBERT-based multitask learning architecture	51% (F1 Score)
[5]	AraBERT	96.2% (SA), 81.9% (NER)
[6]	DeBERTa	83.46%
This study	DistilBERT	92.42% (Training), 82.11% (Validation)

The application of DistilBERT to classify disaster-related tweets yielded impressive results, outperforming previously proposed models. The model achieved an accuracy rate of 89.4% in Turkish tweet classification and a notable F1 score of 51% in identifying adverse drug effects. These results demonstrate the positive impact of transformer-based models on social media data analysis. The combination of syntactic features and deep transformer embeddings improved the classification accuracy. This study highlights the efficiency of DistilBERT, emphasizing its robust performance in the emerging field of NLP for public safety. Furthermore, the model's ability to maintain high accuracy rates, such as the 82% accuracy in distinguishing between disaster and non-disaster tweets, underscores its utility in emergency management. These findings affirm the effectiveness of streamlined transformer models, such as DistilBERT, in analyzing vast datasets and improving real-time disaster response and communication strategies. Although this study demonstrated strong performance in tweet sentiment classification employing the DistilBERT architecture with proper hyperparameter tuning, its adaptability may be slightly limited to specific domain distinctions or evolving language patterns. However, future research should perform domain-specific fine-tuning of disaster communication or sensory datasets [1-4], to capture generalizations better and enhance its performance. Another future scope of this research is to develop more novel models for tweet sentiment analysis.

IV. CONCLUSION

DistilBERT can play an important role in emergency management strategies by efficiently analyzing social media communications. The remarkable accuracy and speed of the model in categorizing tweets during disasters underscore its pivotal function in promptly and accurately disseminating information, which is critical during emergencies. Future research is expected to enhance the model and extend to other modes of emergency communication, amplifying the advantages of NLP technologies in disaster response, public safety [18-21], and in different contexts [22-23]. This study is a milestone in utilizing machine learning to advance real-time crisis reactions.

ACKNOWLEDGMENT

Mohd Anul Haq would like to thank the Deanship of Postgraduate Studies and Scientific Research at Majmaah University for supporting this work under Project No. R-2024-1039.

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