Texas A&M University - Commerce

Department of Computer Science

Machine Learning for Disaster Detection through Twitter Analysis

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May 7, 2024

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Abstract

Twitter has become a crucial medium for people to use their smartphones to provide real-time views of events in the context of modern disaster communication. The difficulty, therefore, lies in programmatically separating the language used in tweets to convey metaphors from actual news of calamities. In order to determine if a tweet is indeed connected to a crisis, this study presents a machine learning algorithm. The suggested approach uses a painstakingly hand- classified dataset of 10,000 tweets and combines vectorization, classification, and NLP models to improve prediction accuracy. By tackling the challenges presented by metaphorical language, this research helps to construct a sophisticated machine learning framework that can determine the genuine nature of tweets connected to emergencies.

Keywords: twitter, real time, text analysis, NLP, disaster detection

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List of Abbreviations

SMPCS	School of Mathematical, Physical and Computational Sciences

Chapter 1

Introduction

Twitter has emerged as a ubiquitous platform for event reporting, facilitated by the widespread use of smartphones. This dynamic environment offers unparalleled opportunities for immediate and decentralized communication, especially during critical events such as disasters. The advent of this digital era has underscored the pressing need for effective crisis communication strategies to harness the potential of Twitter as a valuable tool for situational awareness and emergency response.

However, amidst the wealth of real-time data flowing through Twitter feeds, a significant challenge arises in the accurate identification and differentiation of metaphorical expressions from authentic crisis-related information within tweets. Metaphors, while a powerful linguistic tool for expression, often introduce ambiguity and complexity, posing a considerable hurdle in the quest for reliable crisis detection. The inherent nature of metaphorical language requires a nuanced understanding that transcends traditional analytical approaches, demanding innovative solutions to decipher the true intent behind tweets during critical events.

This research embarks on the journey to address this multifaceted challenge by delving into the intricacies of Twitter communication during crises. The aim is to develop a sophisticated machine learning framework capable of distinguishing between metaphorical language and genuine crisis-related information. Leveraging the prevalence of smartphones and the instantaneous nature of Twitter reporting, this study seeks to contribute to the advancement of crisis communication strategies, fostering a more effective and accurate response to emergencies in the digital age.

1.1 Background

The motivation stems from the critical need for effective crisis communication strategies in utilizing Twitter as a valuable tool for situational awareness and emergency response.

The central challenge lies in accurately discerning metaphorical expressions from genuine crisis-related information within tweets. Metaphors, while powerful for expression, introduce ambiguity, posing a significant hurdle to reliable crisis detection. This project addresses this challenge through the development of a sophisticated machine learning framework, drawing on established classification algorithms with intentional omission of specific names for flexibility. Hyperparameter tuning and model selection are explored for optimization. Concurrently, Natural Language Processing (NLP) models capture contextual nuances to enhance metaphorical language understanding.

1.2 Problem statement

The significant challenge in the realm of disaster monitoring involves distinguishing disaster-related tweets from general Twitter content. This study aims to develop a machine learning algorithm capable of addressing this challenge and accurately determining if a tweet is genuinely connected to a crisis.

1.3 Aims and objectives

Aims: The primary aim of this project is to enhance the field of disaster monitoring on Twitter by developing a sophisticated machine learning framework. The goal is to accurately distinguish tweets related to disasters from the broader spectrum of general content on the platform. Through this endeavor, we seek to contribute to the improvement of crisis communication strategies in the digital age.

Objectives: Implement data exploration and preprocessing techniques to ensure the dataset is prepared for training and evaluation. Explore and apply various machine learning classification algorithms for the effective categorization of tweets, emphasizing the optimization of hyperparameters and model selection. Incorporate Natural Language Processing (NLP) models to capture contextual nuances, enhancing the understanding of metaphorical language within tweets. Evaluate the performance of the developed framework using rigorous metrics to ensure accuracy and reliability in distinguishing disaster-related tweets. Provide insights and recommendations for advancing crisis communication strategies based on the project outcomes.

1.4 Solution approach

The solution approach consists of distinct stages, including data collection, exploration, preprocessing, and the implementation of algorithms for classification and NLP.

1.4.1 Data Collection, Exploration, and Preprocessing

Data Exploration: Comprehensive exploration is conducted to understand the characteristics of the dataset, including the distribution of metaphorical expressions and crisis-related content. **Preprocessing:** Textual data undergoes preprocessing, including tokenization, stemming, and handling of special characters, to prepare it for subsequent stages.

1.4.2 Implementation of Algorithms

Established machine learning classification algorithms are implemented to effectively classify tweets. Hyperparameter tuning and model selection are explored to optimize performance. NLP models are implemented to capture contextual nuances and improve the understanding of metaphorical language in tweets.

1.5 Summary of contributions and achievements

This research contributes a sophisticated machine learning framework capable of distinguishing metaphorical language from genuine crisis-related information on Twitter. Achievements include the development of a robust algorithm, leveraging a hand-classified dataset for effective model training.

1.6 Organization of the report

The report follows a structured format, exploring background, problem statement, solution approach, detailed methodologies, results, discussions, and conclusions.

Chapter 2

Literature Review

Recognizing the imperative for automated solutions to distinguish genuine disaster-related tweets from metaphorical or unrelated content, the research gets crucial reference, aiding in exploring effective approaches and refining the accuracy of disaster-related tweet prediction models from this Kaggle competition Addison Howard (2019) Phil Culliton (2019). With widespread smartphone use, Twitter becomes a primary source for disaster-related information. Utilizing a dataset of 10,000 hand-classified tweets, the goal is to employ machine learning models for binary classification and NLP to predict tweets genuinely related to disasters.

2.1 Related Work

In the research Chanda (2021) extensive evaluation of Deep Learning methods for classifying disaster-related tweets. Identification of preprocessing steps, emphasizing named entity substitution.Performance analysis of custom neural networks and Transformer models.Emphasis on practical application potential for automatic disaster detection. BERT is used in Deb and Chanda (2022) where exploration of Twitter's real-time data for disaster identification and challenges in manual data processing due to volume is elaborated. Evaluation of BERT embeddings' superiority in disaster prediction, compared to traditional word embeddings. Discussion on opportunities and challenges of BERT embeddings in Twitter sentiment analysis. Detailed analysis for various algorithms are explored in Fontalis et al. (2023) Theoretical basis of various ML algorithms for tweet analysis (BNB, MNB, LR, KNN, DT, RF).Process flow from dataset import to model training, emphasizing the importance of Exploratory Data Analysis (EDA). Selection of ML models based on suitability, using Wordclouds for identifying relevant words.Explanation of Bayesian algorithms, logistic regression, decision tree, and random forest usage.Iparraguirre-Villanueva et al. (2023)Exploration of BERT embeddings' effectiveness in disaster prediction on social media. Overview of challenges in manual disaster identification due to data volume. Application of different word embeddings (BOW, context-free, contextual) in disaster prediction models. Utilization of embeddings in both traditional ML methods and neural network-based models.In Saddam et al. (2023)Studies introduce normalization processes for words with similar meanings. Stemming, using the Indonesian literary library in Python, maximizes text processing efficieny. Machine learning involves labeling real opinions, crucial for SVM model training. SVM models, especially for multiclass classification, are discussed for sentiment analysis. K- Fold Cross Validation ensures robust testing, evaluating accuracy, precision, recall, and F- score. Confusion matrices aid in a comprehensive understanding of model performance.

2.2 Critique of the review

Existing research demonstrates the effectiveness of advanced techniques such as deep learning models and contextual embeddings for disaster-related sentiment analysis. Critique emphasizes the need for continuous improvement in addressing challenges related to bias mitigation and contextual understanding.

2.3 Summary

The literature review underscores the significance of sophisticated preprocessing techniques, advanced text processing, and the application of machine learning models for disaster-related sentiment analysis on Twitter. Key findings highlight the potential of deep learning and contextual embeddings in achieving accurate disaster detection, with practical implications for real-world applications. Continuous improvement is encouraged to address existing challenges and further enhance the reliability of sentiment analysis systems.

Chapter 3

Methodology

3.1 Working with the Tweets Dataset

3.1.1 Explorartory Data Analysis

Number of Words in Tweets: To understand the distribution of the number of words in tweets, we plotted histograms for disaster and not-disaster tweets. The histogram for tweets shows a peak around 15-20 words. Also histogram indicates that not disaster-related tweets may be slightly longer scentences on average compared to non-disaster tweets.

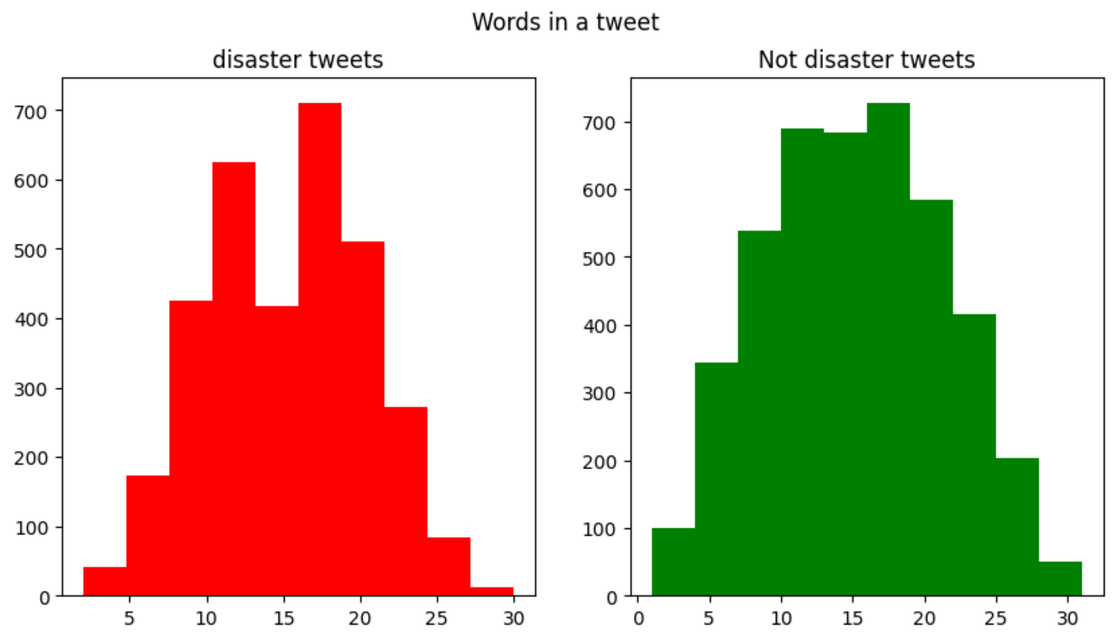

Figure 3.1: Number of words in the tweets based on class

Punctuations in Tweets: We analyzed the usage of punctuations in tweets, separating disaster and non-disaster tweets. The histograms displayed the frequency of various punctuation marks such as commas, exclamation marks, and hashtags. Disaster tweets tend to have more question marks and hashtags compared to non-disaster tweets, suggesting a more urgent or expressive tone.

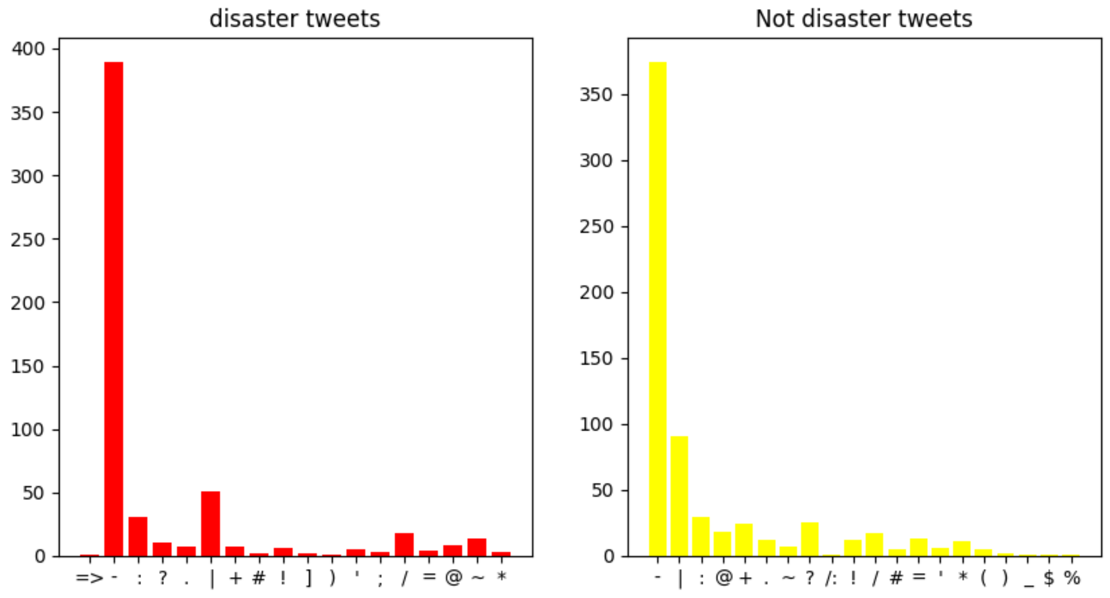

Figure 3.2: Punctuations in the tweets based on class

Bigrams Analysis: Bigrams analysis revealed common pairs of words occurring together in tweets. The bigrams showed the preposition of the places like "in the", "on the". "to be",indicating discussions about readiness and safety measures. "for the" bigram suggesting discussions about response efforts and support for affected individuals. This analysis provides insights into the topics and contexts discussed in disaster-related content.

Notably, the bigram "http co" appeared frequently, indicating the presence of URLs and links that require cleaning and removal from the tweet text. Handling these URLs is crucial as they often do not contribute to the analysis of tweet content and can introduce noise.

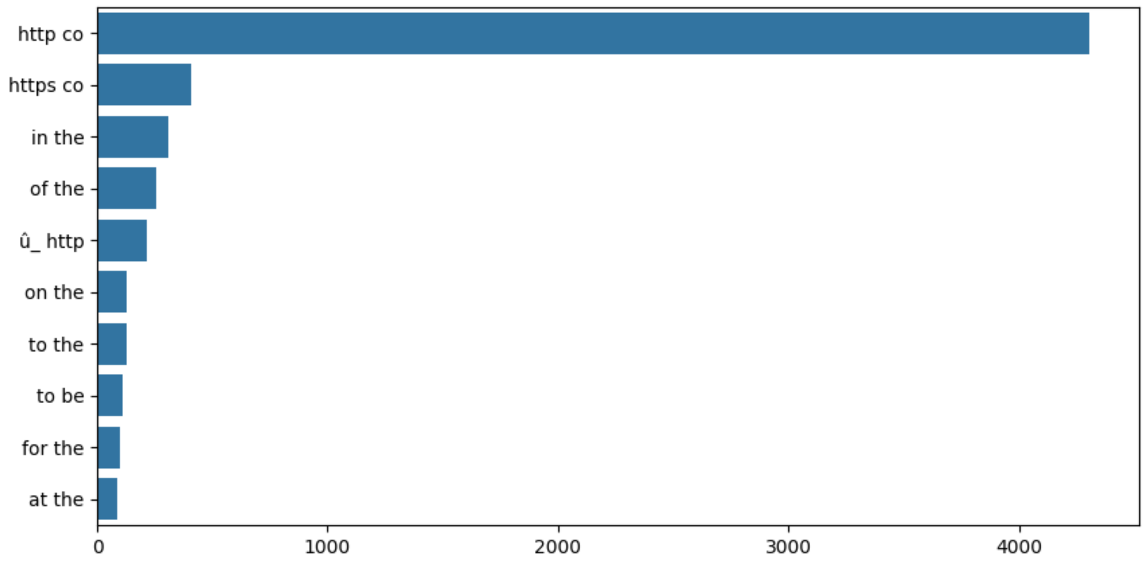

Figure 3.3: Bigrams in the tweet

Common Words in Tweets: By identifying the most common words, you can gain insights into the overall themes and topics present in the tweets. This helps in understanding the nature of the data and what it predominantly talks about. In some cases, analyzing common words can also help in quality assurance by identifying anomalies, spammy content, or irrelevant data that might need further investigation or filtering.

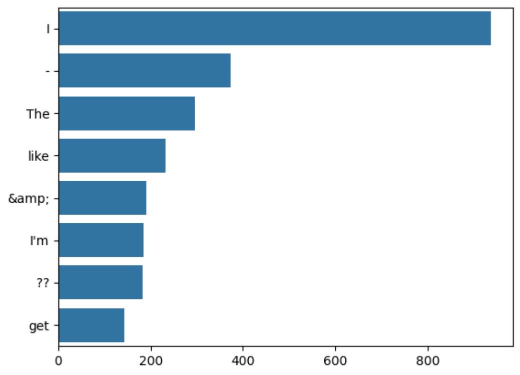

Figure 3.4: Common words in the tweets

3.1.2 Data Cleaning

Removing URLs We started by removing URLs from the tweet text as they often don't contribute to the analysis of tweet content and can introduce noise.

Removing Punctuations Next, we removed punctuations such as commas, periods, and exclamation marks from the text. This step helps in standardizing the text data and focusing on the actual words and meanings in the tweets.

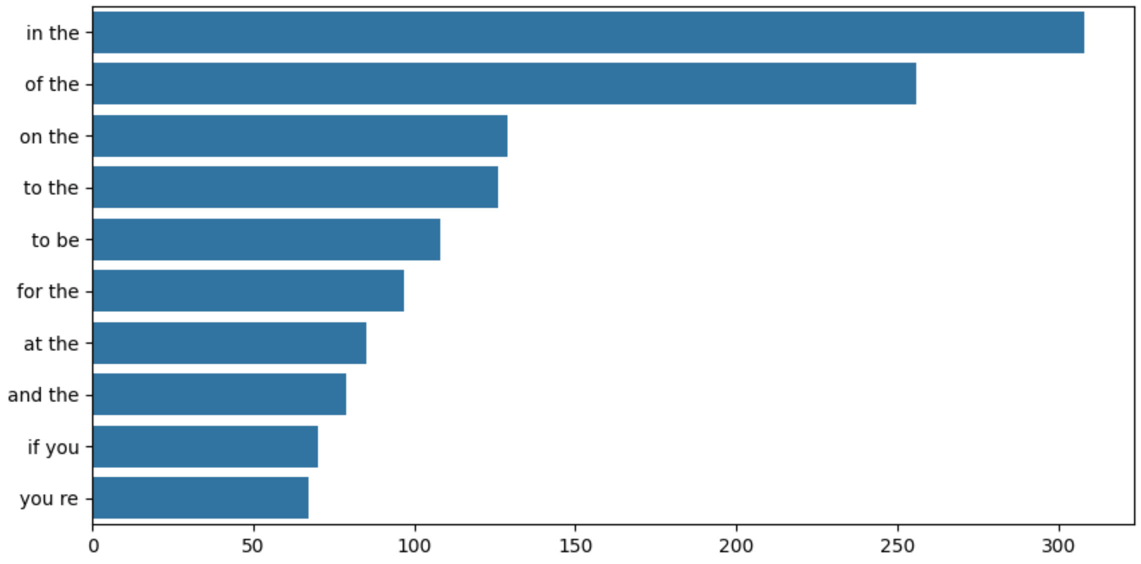

Figure 3.5: Bigram after datacleaning

Word Cloud after Data Cleaning After data cleaning, we generated a word cloud to visualize the most common words in disaster-related tweets. This visualization helps in understanding the key themes and topics prevalent in the cleaned tweet data. Using a word cloud and bar plot, we identified the most common words in disaster-related tweets. Terms like "fire," "disaster, "shelter" appeared prominently, reflecting the focus on urgent situations and crises in these tweets.

These exploratory data analysis and data cleaning steps are crucial for preprocessing the tweet data and gaining insights into the characteristics of disaster-related content on social media platforms.

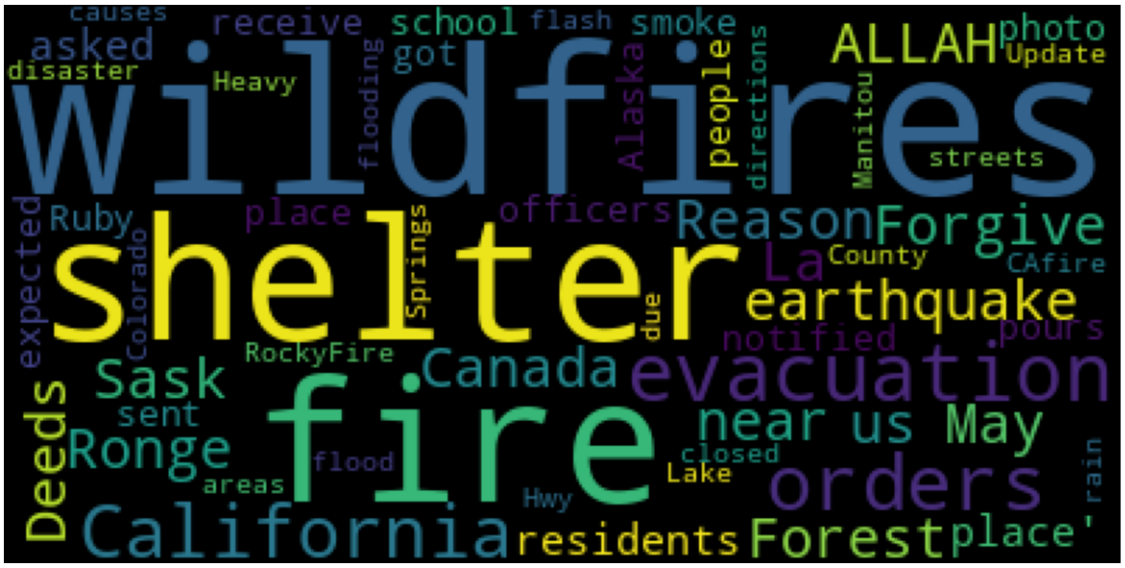

Figure 3.6: Wordcloud for tweets data

3.2 Algorithms

3.2.1 Logistic regression for tweet classification

Logistic regression is a linear classification algorithm used extensively for binary classification tasks, where the goal is to predict a binary outcome (e.g., disaster or non-disaster) based on input features (e.g., tweet text).

Text Preprocessing and Vectorization: Text Tokenization:The tweet text is tokenized, breaking it down into individual words or tokens. Count Vectorization: The CountVectorizer is used to convert the tokenized text into numerical vectors. Each tweet is represented by a vector where each element corresponds to the count of a specific word in the tweet.

Dataset Splitting: The dataset is split into training and validation sets using a predefined ratio (e.g., 80 percent for training, 20 percent validation). This separation allows us to train the model on a subset of data and evaluate its performance on unseen data.

Training Process: The model is trained using the training data and their corresponding vector representations. During training, the model adjusts its coefficients to minimize the logistic loss function and improve classification accuracy.

Performance Evaluation: The model's accuracy on the training set is calculated to assess its performance on data it has been trained on. Training accuracy indicates how well the model fits the training data. The model's accuracy on the validation set is computed to evaluate its generalization ability to unseen data. Validation accuracy helps determine if the model can make accurate predictions on new tweets.

Confusion Matrix Analysis:

The confusion matrix is generated to visualize the model's predictions on both the training and validation sets. It consists of four quadrants: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN).

F1 Score Calculation:

The F1 score, which combines precision and recall, is calculated based on the confusion matrix. It provides a single metric to assess the model's overall performance, particularly useful for imbalanced datasets.

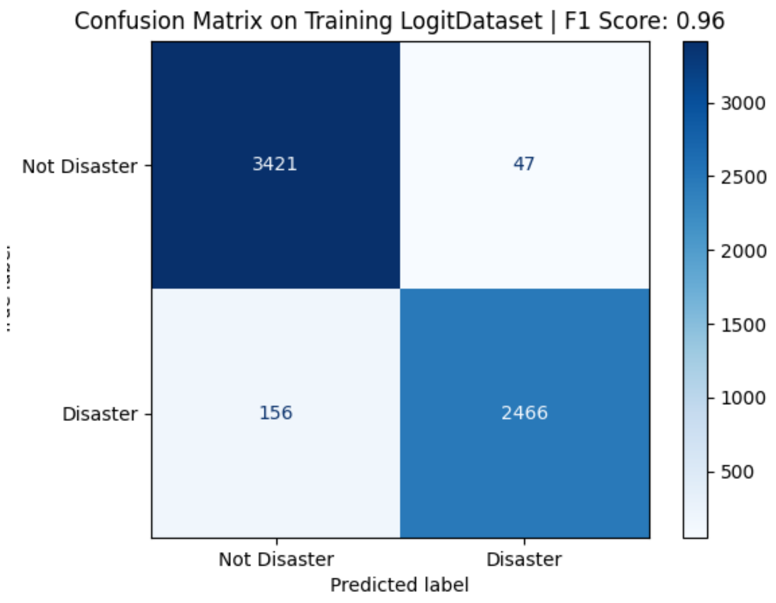

Figure 3.7: Wordcloud for tweets data

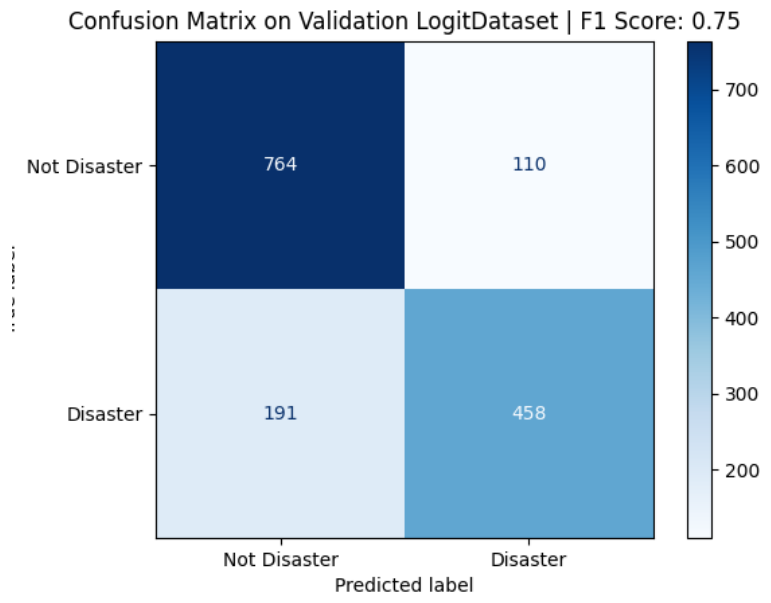

Figure 3.8: Wordcloud for tweets data

3.2.2 DistilBERT for tweet classification

DistilBERT is a state-of-the-art transformer-based model designed for natural language processing (NLP) tasks, particularly well-suited for tweet classification, such as identifying disaster-related tweets from non-disaster ones.

DistilBERT Model Configuration Preprocessing: The DistilBERT model uses a preprocessor specifically tailored for tweet analysis, with a preset configuration for handling tweet sequences up to 160 tokens in length.

Model Architecture:

The DistilBERT classifier is based on the "distil bert base en uncased" preset, which utilizes a distilled version of the BERT (Bidirectional Encoder Representations from Transformers) architecture. This architecture incorporates transformer layers to process input tokens, capturing contextual relationships between words and phrases in the tweet. The "distilbert-base-uncased" denotes a base-sized variant of the DistilBERT model that was trained using uncased text data. This model finds widespread application across a range of natural language processing tasks like text classification, sentiment analysis, question answering, among others.

Training the model: The training setup includes a batch size of 20, a training split of 80, and a validation split of 20 to ensure robust model evaluation. The number of training examples is determined dynamically from the dataset, and the number of steps per epoch is calculated based on the batch size and training examples. To maintain reproducibility, a random seed of 0 is set before training the model, ensuring consistent results across different runs.

Model Summary

The DistilBERT model summary provides insights into the model architecture, including the number of layers, parameters, and output shapes. This summary aids in understanding the complexity and capabilities of the DistilBERT classifier for tweet analysis. The classifier is trained over 7 epochs, optimizing the model using the Adam optimizer with a learning rate of 1e-5. During training, performance metrics such as accuracy and loss are monitored to assess the model's learning progress. Evaluation includes validating the model's performance on a separate validation set to gauge its ability to generalize to unseen data.

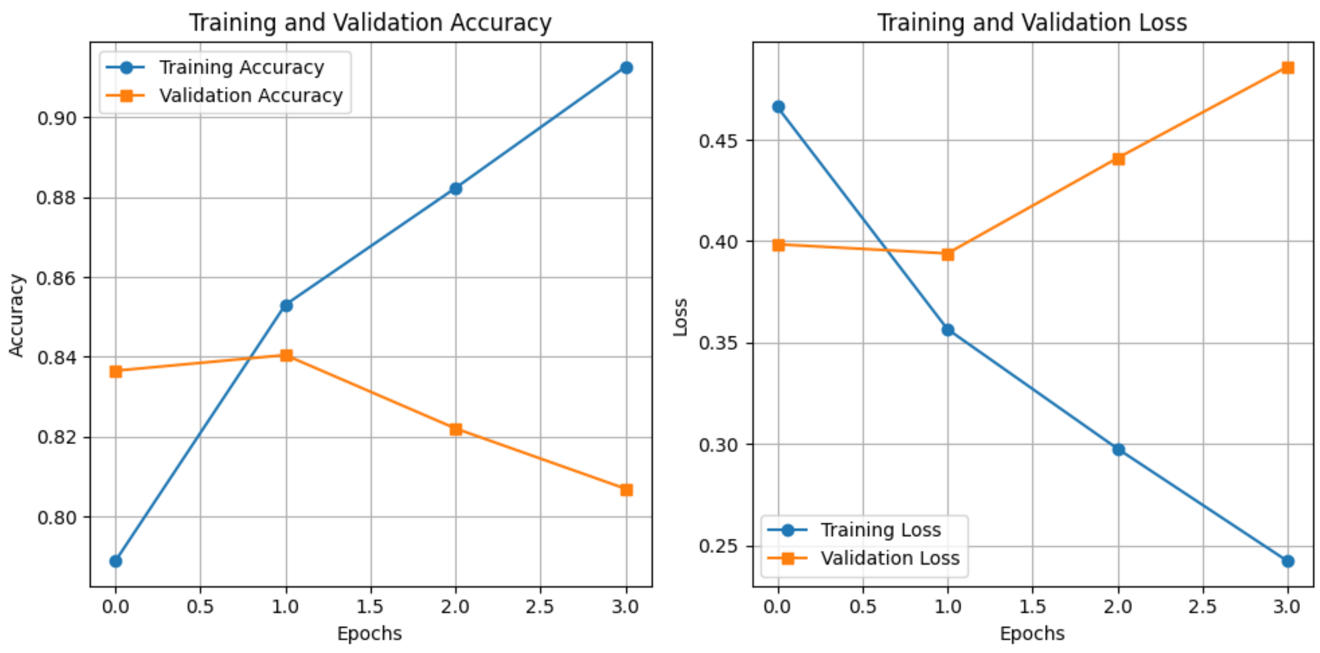

Figure 3.9: Distilbert with parameter setting accuracy and loss graph

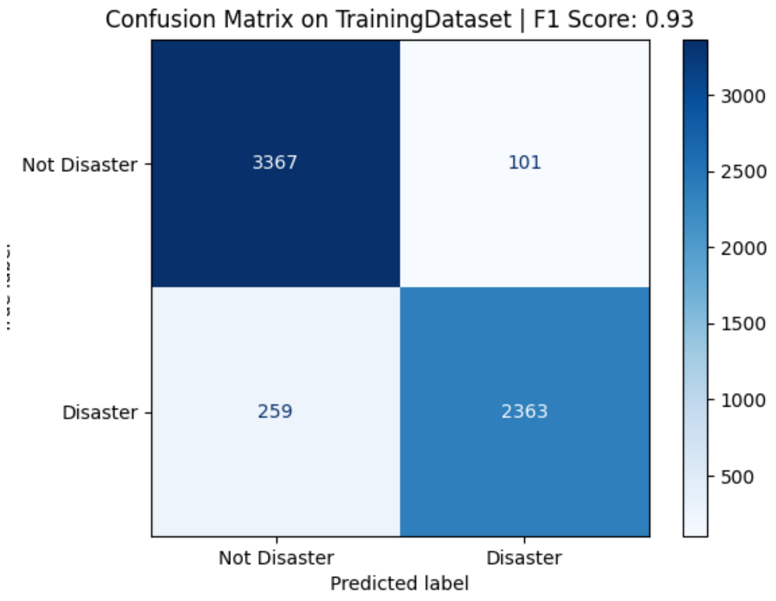

Figure 3.10: Distilbert with parameter setting

DistilBert with Autotune

Efficient data loading and processing are critical aspects of training deep learning models, especially when working with large datasets. TensorFlow, a popular deep learning framework, provides the AUTOTUNE feature to dynamically optimize data loading and preprocessing operations, enhancing training performance and resource utilization.

The Need for Optimization:

In deep learning workflows, data loading and preprocessing pipelines can become bottlenecks, slowing down model training and inference. These pipelines involve tasks such as reading data from storage, applying transformations (e.g., augmentation, normalization), and preparing batches for training. Traditional approaches often involve static configurations for these operations, which may not fully exploit system resources or adapt to varying workloads.

Understanding AUTOTUNE:

TensorFlow's AUTOTUNE feature addresses these challenges by enabling dynamic optimization of data loading and processing. When applied to dataset operations, AUTOTUNE allows TensorFlow to automatically adjust parameters such as parallelism, prefetching, and buffer sizes based on system conditions and available resources.

By setting prefetch(tf.data.AUTOTUNE) on these datasets, TensorFlow dynamically optimizes data loading and preprocessing operations during model training.

Benefits of AUTOTUNE:

Optimized Parallelism: AUTOTUNE adjusts parallelism settings to exploit multi-core CPUs or GPUs efficiently, reducing data loading bottlenecks and improving training throughput. Dynamic Prefetching: TensorFlow prefetches batches of data ahead of time, overlapping data loading with model computation. AUTOTUNE optimizes the prefetch buffer size based on system performance, reducing training latency. Resource Utilization: By adaptively tuning parameters such as buffer

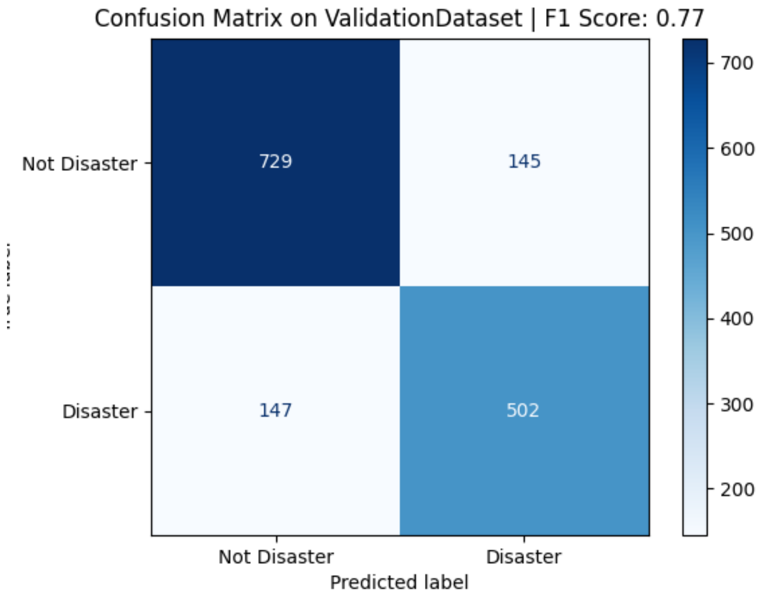

Figure 3.11: Distilbert with parameter setting

sizes and parallelism, AUTOTUNE optimizes resource utilization, preventing underutilization or resource contention during training. Conclusion:

The use of AUTOTUNE in TensorFlow significantly enhances the efficiency of data loading and preprocessing pipelines in deep learning workflows. By dynamically optimizing parameters based on system conditions, AUTOTUNE improves training performance, accelerates convergence, and maximizes resource utilization, making it a valuable tool for deep learning practitioners. float

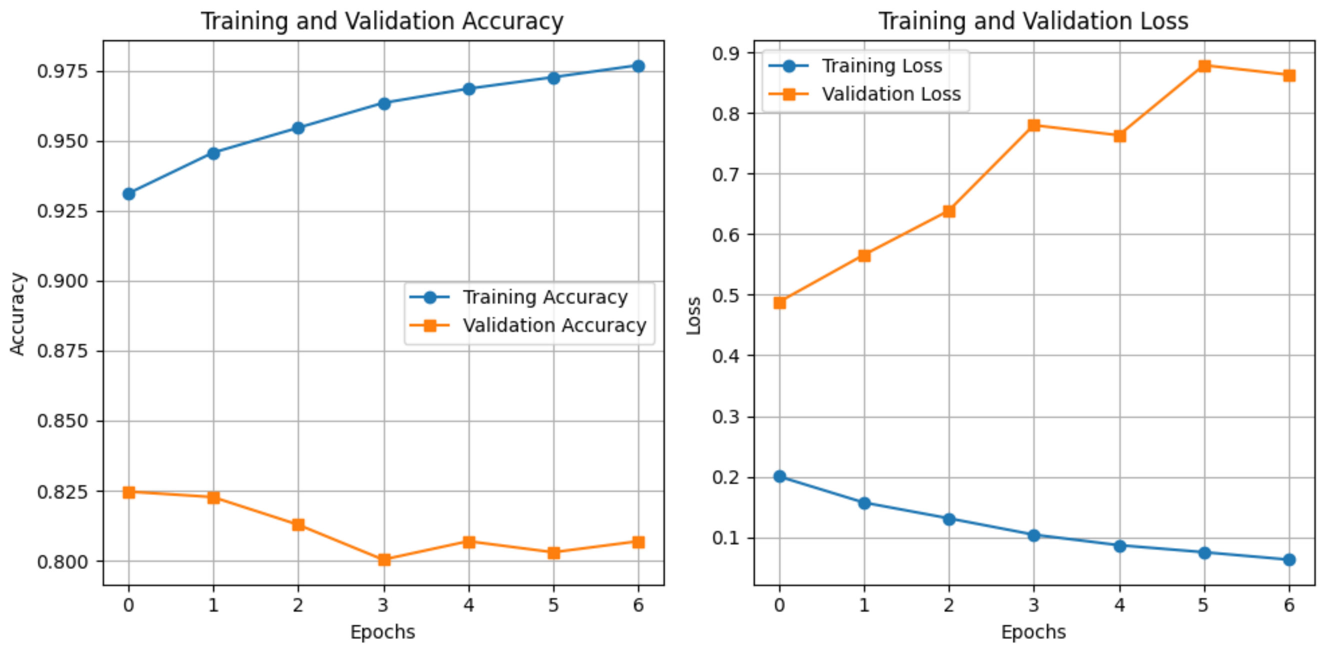

Figure 3.12: Distilbert with autotune accuracy and loss graph

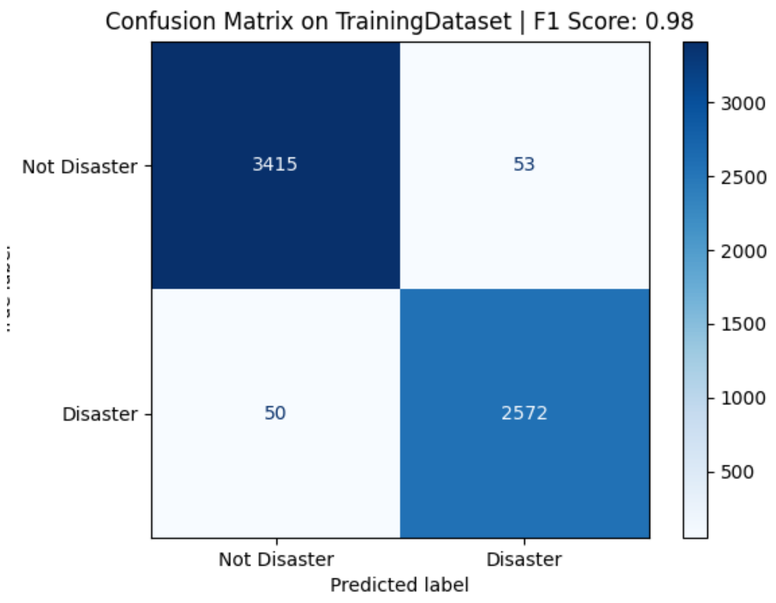

Figure 3.13: Distilbert with autotune

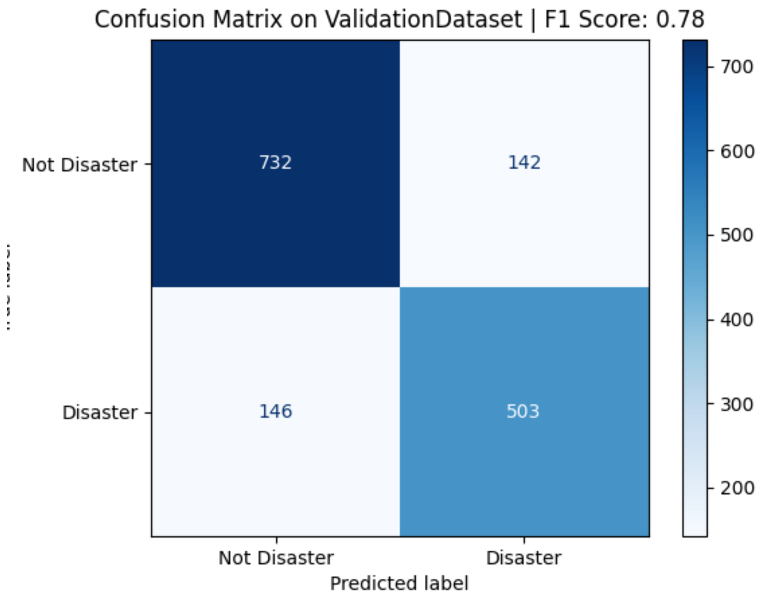

Figure 3.14: Distilbert with autotune

3.3 Best Accuracy of DistilBERT

By examining the graphs, it's evident that the validation accuracy peaks at EPOCH=2. Consequently, we trained the model specifically with EPOCH=2, resulting in an accuracy boost to 81 percent. This indicates a case of overfitting due to excessive training, as the model's performance improved initially but then started to deteriorate.

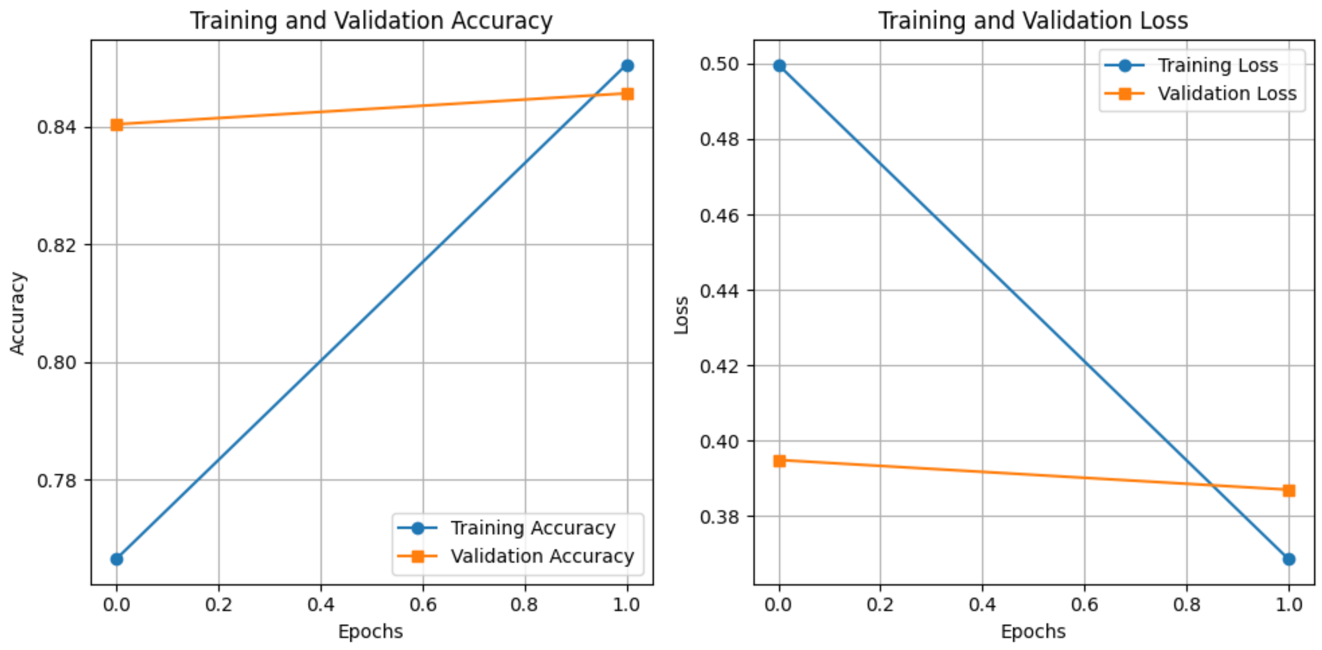

Figure 3.15: Distilbert with EPOCH=2

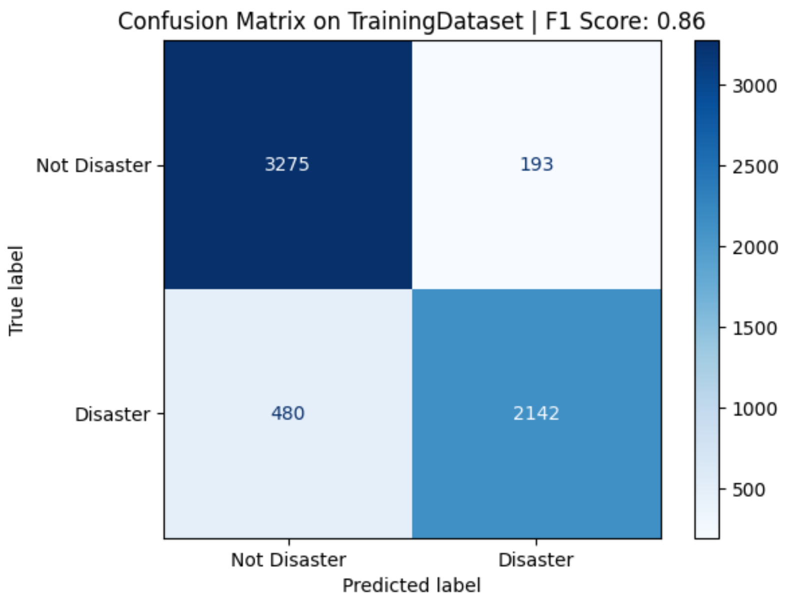

Figure 3.16: Distilbert with EPOCH=2

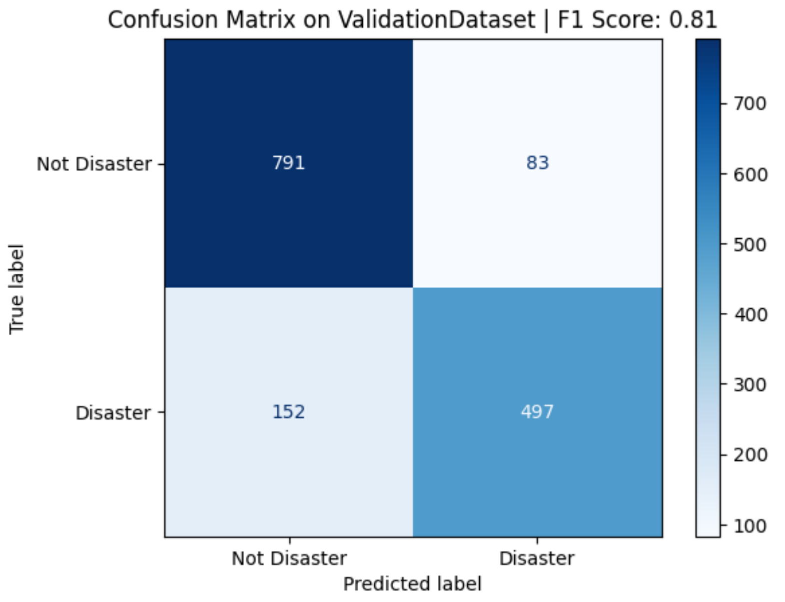

Figure 3.17: Distilbert with EPOCH=2

3.4 Summary

Logistic regression is suitable for simpler text classification tasks, offering interpretability and efficiency, whereas DistilBERT excels in capturing complex patterns and semantics, albeit at the cost of increased computational resources and complexity. The choice between the two depends on the task complexity, dataset size, interpretability requirements, and available computational resources.

The DistilBERT model benefits from this optimization, ensuring that computational resources are utilized effectively during training and inference. Overall, the configuration and training setup of the DistilBERT model for tweet analysis demonstrate a methodical and optimized approach, leveraging state-of-the-art NLP techniques to achieve accurate classification of disaster-related tweets.

Chapter 4

Results

The training and evaluation of the logistic regression model yielded promising results, with a training accuracy of 96 percent and a validation accuracy of 75 percent. This indicates that the model performed well in learning from the training data but showed a slight decrease in accuracy when tested on unseen validation data. On the other hand, the DistilBERT model achieved a training accuracy of 93 percent and a validation accuracy of 77 percent, showcasing its capability in handling complex textual data and performing consistently across both training and validation sets.

Further optimization using DistilBERT with Explicitly applied AUTOTUNE led to significant improvements, with a training accuracy of 98percent and a validation accuracy of 78 percent. The dynamic optimization provided by AUTOTUNE played a crucial role in enhancing the model's generalization ability, allowing it to maintain high accuracy on unseen data while leveraging efficient resource utilization.

Table 4.1: Performance Comparison of Different Models

model	Traning score	Validation score
Logistic regression	96	75
Distilbert with EPOCH=4	93	77
Distilbert with EPOCH=7	98	78
Distilbert with EPOCH=2	86	81

AUTO = tf.data.experimental.AUTOTUNE and explicitly applying tf.data.AUTOTUNE. both methods aim to achieve similar optimization goals without imposing a noticeable overhead on training time.

Chapter 5

Discussion and Analysis

5.1 DistilBERT

ADAM: When working on binary classification tasks in NLP like sentiment analysis (positive/negative), spam detection (spam/ham), or topic classification (relevant/irrelevant), the selection of optimizer plays a crucial role in shaping the training process and model performance. Here Adam optimizer is used with DistilBert, it extensively utilized and generally exhibits strong performance across various NLP tasks involving binary classification. Blends the advantages of adaptive learning rates and momentum, proving effective in handling sparse gradients and noisy data. Converges swiftly and manages large-scale datasets efficiently. Adam is often a reliable and efficient default optimizer for binary classification tasks in NLP. Its robustness, quick convergence, and good generalization make it a recommended choice.

Batch Size: This parameter decides how many training examples are utilized in each iteration of gradient descent within a single epoch. For instance, if your batch size is set to 32, the model adjusts its weights after handling 32 training examples. A larger batch size may accelerate training but could demand more memory, while a smaller batch size could yield a more precise gradient estimate albeit potentially slowing down training.

Steps per Epoch: Calculated from the total training examples and the batch size, steps per epoch indicates the iterations necessary to complete one epoch. For example, if you have 1000 training examples and a batch size of 32, you'd compute 1000 / 32 = 31.25 steps per epoch. In practice, this number is rounded down to the nearest whole number, making it 31 steps per epoch in this scenario.

Epoch: An epoch signifies a complete traversal through the entire training dataset. In each epoch, the model undergoes iterations equal to the steps per epoch, with each iteration handling a batch of training examples dictated by the batch size. Once all these iterations are done, one epoch concludes.

For distilBERT, When you employ AUTO = tf.data.experimental.AUTOTUNE in TensorFlow, the system autonomously fine-tunes the data loading process based on the available hardware, managing aspects like parallel reads, prefetching, and batching. This optimization aims to maximize CPU and GPU usage, potentially resulting in quicker data processing and training compared to setting these parameters manually.

Manually incorporating tf.data.AUTOTUNE into your data pipeline operations—like prefetching and parallel reads—can achieve a similar optimization. However, it necessitates a grasp of hardware capabilities and the adjustment of parameters accordingly.

Chapter 6

Conclusions and Future Work

6.1 Conclusions

In conclusion, the results highlight the effectiveness of advanced machine learning techniques, particularly DistilBERT, in classifying disaster-related tweets. The logistic regression model, while providing a good baseline, was outperformed by DistilBERT, especially when optimized with AUTOTUNE. This underscores the importance of leveraging state-of-the-art models and dynamic optimization strategies to achieve high accuracy and robustness in disaster detection systems based on Twitter data. The findings suggest that DistilBERT, with its advanced natural language understanding capabilities and efficient resource utilization through AUTOTUNE, is a preferred choice for real-time disaster detection and response.

6.2 Future work

Future Work is Implementing MLOps for Enhanced Disaster Detection:

As a researcher in the field of disaster detection through Twitter analysis, there are several avenues for future work that can significantly enhance the effectiveness and efficiency of the developed machine learning framework. One promising direction is the implementation of MLOps (Machine Learning Operations) practices to streamline the deployment, monitoring, and management of machine learning models in production environments.

Continuous Model Monitoring: Implementing automated monitoring tools to continuously track the performance of the deployed machine learning models. This includes monitoring metrics such as accuracy, precision, recall, and F1-score in real-time, detecting any drift or degradation in model performance, and triggering alerts for timely intervention.

Automated Retraining Pipelines: Developing automated pipelines for model retraining using fresh data. This involves integrating data pipelines that fetch new tweet data, preprocess it, and feed it into the retraining process. Automated retraining ensures that the model remains up-to-date with evolving language patterns and crisis-related trends on Twitter.

Scalability and Elasticity: Designing scalable and elastic infrastructure to handle varying workloads and sudden spikes in Twitter activity during emergencies. Leveraging cloud services and containerization technologies like Kubernetes to dynamically allocate resources based on demand, ensuring smooth performance during peak periods.

Model Versioning and Rollbacks: Implementing version control for machine learning models to track changes, compare performance across different versions, and facilitate easy rollbacks in case of model regressions or unforeseen issues. Versioning enables researchers to experiment with new algorithms and improvements without disrupting the production system.

Security and Privacy Considerations: Incorporating robust security measures to protect sensitive data within the machine learning pipelines. This includes encryption techniques, access control mechanisms, and compliance with data privacy regulations such as GDPR and CCPA to ensure ethical handling of user-generated content on Twitter.

Integration with External APIs: Integrating the disaster detection system with external APIs and data sources for enhanced situational awareness. This includes accessing real-time geospatial data, weather information, social media sentiment analysis APIs, and emergency response systems to provide comprehensive insights during crises.

By embracing MLOps practices, researchers can not only improve the reliability and accuracy of disaster detection models but also ensure their seamless integration into operational workflows for effective real-time decision-making and emergency response. MLOps enables continuous learning, agility, and scalability, making it a valuable approach for advancing disaster communication strategies in the digital age.

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Appendix A

An Appendix Chapter (Optional)

Some lengthy tables, codes, raw data, length proofs, etc. which are **very important but not essential part** of the project report goes into an Appendix. An appendix is something a reader would consult if he/she needs extra information and a more comprehensive understating of the report. Also, note that you should use one appendix for one idea.

An appendix is optional. If you feel you do not need to include an appendix in your report, avoid including it. Sometime including irrelevant and unnecessary materials in the Appendices may unreasonably increase the total number of pages in your report and distract the reader.

Appendix B

An Appendix Chapter (Optional)

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