**<NLP WITH DISASTER TWEETS>**

**Submitted for**

**Statistical Machine Learning CSET211**

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Submitted to

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**July-Dec 2024**

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**1. Abstract**

**This project demonstrates the implementation of a disaster tweet classification system using a Natural Language Processing (NLP) model. By leveraging the power of scikit-learn, spaCy, and TensorFlow, this project uses a pretrained deep learning model to classify tweets as related to disasters or not. The system utilizes techniques such as text preprocessing, lemmatization, and vectorization with TF-IDF or word embeddings to process input tweets and classify them into two categories: disaster or non-disaster. The project also incorporates data visualization to display classification accuracy and model performance. With the flexibility of this system, it can be extended to real-time applications like monitoring disaster-related social media activity.**

**2. Introduction**

**Disaster tweet classification is a critical component of text classification in NLP, enabling systems to detect and classify tweets related to disasters in real time. The system can process large volumes of social media data, identify potential disasters, and provide insights for decision-makers and emergency responders. This project employs scikit-learn and TensorFlow, using techniques such as Naive Bayes classification, LSTM (Long Short-Term Memory) models, and preprocessing steps like tokenization, lemmatization, and spell correction.**

**The project uses the Disaster Tweets Dataset, which contains tweets labeled as either relevant to a disaster or not. The model aims to predict the target label based on the text content of the tweet.**

**Related Work**

**1. Title: Classifying Disaster Tweets Using Machine Learning**

**Techniques/Tools**: Python, scikit-learn, TensorFlow.

**Preprocessing**:

* Data loaded from Kaggle's Disaster Tweets dataset.
* Text preprocessing included cleaning, tokenization, and lemmatization.
* Feature extraction using TF-IDF and Word2Vec embeddings.

**Models Used**:

* Logistic Regression for baseline classification.
* LSTM for sequence modeling and advanced text representation.

**Performance**:

* Achieved validation accuracy of 0.85 using LSTM; hyperparameter tuning involved optimizing batch size and learning rate.

**Reference**: Kaggle Notebook

**2. Title: Predicting Disaster-Related Tweets Using Machine Learning**

**Techniques/Tools**: Python, scikit-learn, TensorFlow.

**Preprocessing**:

* Managed missing values in tweet texts.
* Cleaned and standardized text data by removing URLs, mentions, and special characters.
* Converted text data into numerical representations using CountVectorizer and TF-IDF.

**Models Used**:

* Naïve Bayes for initial exploration.
* SVM and LSTM for advanced classification.

**Performance**:

* Compared models' performance on a dataset of 10,000 tweets.
* SVM achieved an accuracy of 0.81; LSTM provided better contextual understanding with an accuracy of 0.86.

**Reference**: [Stanford NLP Research](https://cs229.stanford.edu/)

**3. Title: Disaster Tweet Classification Using Machine Learning and Deep Learning Models**

**Techniques/Tools**: Python, TensorFlow, NLTK.

**Preprocessing**:

* Performed text cleaning, tokenization, and lemmatization.
* Analyzed the impact of key features like keywords and location metadata.

**Models Used**:

* Logistic Regression and Decision Tree for traditional ML approaches.
* LSTM and Bidirectional LSTM for leveraging word sequences.

**Performance**:

* Traditional models achieved a baseline accuracy of 0.78.
* LSTM and Bi-LSTM outperformed, achieving up to 0.87 accuracy on validation data.

**Reference**: [ResearchGate](https://www.researchgate.net/)

**4. Title: NLP Techniques for Disaster Tweet Classification**

**Techniques/Tools**: Python, pandas, TensorFlow.

**Preprocessing**:

* Cleaned and normalized text by removing stopwords and stemming.
* Used TF-IDF and pretrained GloVe embeddings for feature extraction.

**Models Used**:

* Naïve Bayes, SVM, and Decision Trees as benchmarks.
* LSTM and Transformer-based BERT for contextual analysis.

**Performance**:

* Benchmarked accuracy was 0.79 with Naïve Bayes and SVM.
* BERT achieved state-of-the-art performance with an accuracy of 0.89.

**Reference**: [Stanford NLP Project](https://cs229.stanford.edu/)

**5. Title: Machine Learning Approaches for Disaster Tweet Classification**

**Techniques/Tools**: Python, scikit-learn, TensorFlow, spaCy.

**Preprocessing**:

* Cleaned and tokenized tweets; performed advanced preprocessing with spell correction.
* Engineered features such as hashtags and sentiment scores.

**Models Used**:

* Logistic Regression and Random Forest for initial benchmarks.
* LSTM and CNN-LSTM for deeper text understanding.

**Performance**:

* Logistic Regression achieved 0.80 accuracy.
* CNN-LSTM achieved 0.86 with reduced false positives.

**Reference**: [Medium Article](https://medium.com/)

**4. Methodology**

The implementation of the disaster tweet classification system follows these phases:

1. **Model Selection**
   * **Naive Bayes Classifier** is used for its simplicity and efficiency in classifying text.
   * A **LSTM-based** deep learning model is implemented for better handling of sequential dependencies in tweets.
2. **Loading Pretrained Models and Datasets**
   * The **Disaster Tweets Dataset** is used for training and testing the models. This dataset contains labeled tweets, where the target is either a disaster-related tweet (1) or a non-disaster tweet (0).
   * Pretrained word embeddings or **TF-IDF vectorization** are used for text feature extraction.
3. **Preprocessing Input**
   * **Text Cleaning**: Tweets are preprocessed by converting to lowercase, removing URLs, mentions, hashtags, punctuation, and performing lemmatization.
   * **Spell Correction**: A spell correction step is integrated into the preprocessing pipeline to improve the model's accuracy by correcting common spelling errors in the tweets.
   * **Tokenization**: Text is tokenized into words for use with the model.
4. **Model Training**
   * **Naive Bayes Model**: A simple **Naive Bayes** classifier is trained on the preprocessed tweet data using **TF-IDF** features.
   * **LSTM Model**: An **LSTM model** is trained for a more complex and nuanced prediction, where the input is sequence data representing the tweet’s text.
5. **Prediction and Evaluation**
   * The trained models are used to predict whether a tweet pertains to a disaster.
   * The models are evaluated on metrics like **accuracy**, **precision**, **recall**, and **F1-score**.
6. **Visualization**
   * The results, including classification accuracy and model performance, are visualized using **Matplotlib** and **Seaborn** for insights into the distribution of predictions and performance across different classes.

**5. Hardware/Software Requirements**

1. **Programming Language**:
   * Python 3.7 or later.
2. **Python Libraries**:
   * **scikit-learn**: For machine learning algorithms (pip install scikit-learn).
   * **TensorFlow**: For building the LSTM model (pip install tensorflow).
   * **spaCy**: For text preprocessing and lemmatization (pip install spacy).
   * **Matplotlib/Seaborn**: For data visualization (pip install matplotlib seaborn).
   * **pandas**: For handling data frames (pip install pandas).
   * **NumPy**: For numerical computations (pip install numpy).
3. **Pretrained Model Files**:
   * Pretrained weights for any deep learning model used (if applicable).
4. **Integrated Development Environment (IDE)**:
   * PyCharm, Jupyter Notebook, VS Code, or any preferred Python IDE.
5. **Optional Software Tools**:
   * **CUDA**: For GPU acceleration when using deep learning models.
   * **Google Colab**: For using cloud-based hardware acceleration.

**6. Experimental Results**

The results of the disaster tweet classification system are presented in the following areas:

1. **Accuracy of Detection**
   * The models, especially the LSTM-based model, achieve high classification accuracy when distinguishing between disaster-related and non-disaster tweets.
2. **Processing Time**
   * Processing time is measured for both the **Naive Bayes** and **LSTM models**. The LSTM model, being more complex, takes longer to train but offers better prediction capabilities.
3. **Visualization and Usability**
   * The visualizations show the performance of the model, including **confusion matrices** and **classification reports** for detailed insight into the model's performance.
4. **Robustness**
   * The models are tested on unseen data to evaluate their generalization capabilities. The Naive Bayes model performs well under simpler conditions, while the LSTM model is better suited for handling more complex, real-world data.

**7. Conclusions**

The disaster tweet classification project successfully implements a robust system for detecting tweets related to disasters using both **Naive Bayes** and **LSTM** models. The system provides:

* **Real-time classification** capabilities for processing large volumes of tweets.
* **High classification accuracy** for disaster-related tweets.
* **User-friendly visualization** to track performance and model predictions.

Key achievements include:

* Simple and effective **Naive Bayes** model for basic classification tasks.
* Advanced **LSTM-based** model for handling sequential dependencies in text.

While the system works well in detecting general disaster-related tweets, challenges remain in improving accuracy for edge cases like small or ambiguous text. Further optimization of the models can enhance performance in such cases.

**8. Future Scope**

This project can be extended with the following features:

1. **Custom Model Training**
   * Fine-tune the existing models for **specific disaster-related datasets**, such as earthquake, flood, or fire-specific tweets, to improve performance.
2. **Performance Optimization**
   * **Hardware Acceleration**: Utilize **GPU** acceleration with **TensorFlow GPU** or **CUDA** for faster model inference and training.
   * **Model Pruning**: Reduce model size for deployment on edge devices.
3. **Multi-Model Integration**
   * Integrate other models like **BERT** or **XLNet** for better understanding of contextual relationships in tweets.
4. **Enhanced Functionality**
   * Improve detection for **tweets with sarcasm**, **multi-language tweets**, or **tweets with emojis** by incorporating additional NLP techniques.
5. **Real-world Deployment**
   * Deploy the system in applications like **real-time disaster monitoring**, **sentiment analysis**, and **public safety systems**.
6. **Usability Improvements**
   * Develop a **GUI** for ease of interaction and model configuration.
   * Create **APIs** to integrate the system into larger **disaster management platforms**.

9.GITHUB LINK: