Project Proposal:

Disaster Response and Damage Assessment

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Motivation:

An increasing number of people use Social Media (SM) platforms like Twitter and Instagram to report information about critical emergencies or disaster events. Multimodal data shared on these platforms often contain useful information about a scale of the event, victims and infrastructure damage. This data can provide local authorities and humanitarian organizations with a big picture understanding of the emergency. Moreover, it can be used to effectively and timely plan relief responses.

The assessment of post-disaster damage is crucial for accounting for critical information such as the number of persons missing, injured, deceased, and so on, as well as damage to infrastructure and public property. This information is crucial in directing government funding and attention to the most severely affected communities in order to provide compensation, food, utilities, and emergency medical treatment.

Problem Statement:

In this study, we aim to accomplish the following goals:

1. Use Deep Learning techniques like Transfer Learning, and Multi-Task Learning to improve the performance of humanitarian category classification on the CrisisMMD dataset.
2. Using learned representation from the humanitarian category classification model to analyse the extent of infrastructural damage (severe, mild , little) by fine-tuning the model.
3. Incentivize multiple modalities (text and images) to perform Multi-Model Late Fusion.
4. Evaluate the scalability and effectiveness of the trained models on real-life images of recent disaster events.

Data:

The **CrisisMMD multimodal Twitter dataset** consists of several thousands of manually annotated tweets and images collected during seven major natural disasters including earthquakes, hurricanes, wildfires, and floods that happened in the year 2017 across different parts of the World. The provided datasets include three types of annotations:

1. Informative vs Non-informative

2. Humanitarian Categories

- Affected individuals
- Infrastructure and utility damage
- Injured or dead people
- Missing or found people
- Rescue, volunteering or donation effort
- Vehicle damage
- Other relevant information

3. Damage Severity Assessment
    - Severe Damage
    - Mild Damage
    - Little/No Damage

Data Exploration and Statistics: [dataset]

Table: Disaster types and per-disaster data points

Crisis name	# tweets	# images	# filtered tweets	# sampled tweets	# sampled images
Hurricane Irma	3,517,280	176,972	5,739	4,041	4,525
Hurricane Harvey	6,664,349	321,435	19,967	4,000	4,443
Hurricane Maria	2,953,322	52,231	6,597	4,000	4,562
California wildfires	455,311	10,130	1,488	1,486	1,589
Mexico earthquake	383,341	7,111	1,241	1,239	1,382
Iraq-Iran earthquake	207,729	6,307	501	499	600
Sri Lanka floods	41,809	2,108	870	832	1,025
Total	14,223,141	576,294	36,403	16,097	18,126

Table: Class-wise data distribution [text (left) and image (right)]

Humanitarian		
Affected individuals	472	562
Infrastructure and utility damage	1210	3624
Injured or dead people	486	110
Missing or found people	40	14
Not humanitarian	4549	8708
Other relevant information	5954	2529
Rescue volunteering or donation effort	3293	2231
Vehicle damage	54	304
Total	**16058**	**18082**

Approach:

1. **Data Collection:**
    - Download CrisisMMD v2 dataset
    - Scrape most recent disaster event images based on location and the type of event.

2. **Data Pre-processing:**
    - Images:
        - Filter out relevant and informative images.
        - Apply augmentations to balance the classes.
    - Tweets:
        - Filter out relevant and informative tweets.
        - Remove stop words, punctuations, and URLs.

3. **Data Exploration and Analysis:**
    - Visualize the data to check for possible imbalance and quantitative analysis.
    - Balance the dataset by using upsampling or undersampling based on the data statistics.

4. **Build Deep Learning Models:**
    - Task 1:
        - Train state-of-the-art deep learning models like ResNet-50, and VGG-16 for images and RNN based models for text, for multiclass classification of humanitarian categories.
    - Task 2:
        - Using Transfer Learning, fine-tune ResNet-50, and VGG-16 trained on Task 1 for multiclass classification of damage severity assessment.

5. **Multi-modal Late Fusion:**
    - Using the predictions from the text and image models perform late fusion technique: Custom Decision Policy (Simple Neural network)

6. **Experimentation and HPO:**
    - Tune hyper-parameters, experiment various optimization and normalization techniques to improve the classification performance of the models.
    - Evaluate the model performance using metrics like, accuracy, precision, f1-score, and recall.
    - Visualize the model performance using confusion matrices, training and validation loss/accuracy plots.

7. **Evaluation:**
    - Use the trained model with the best set of parameters to evaluate real-life disaster images scraped from the web to evaluate the scalability and effectiveness of the model for future disasters.

Timeline:

Week	Deliverable
5	Dataset Collection
6	Data pre-processing
7	Data Exploration and Analysis
8	Build Deep Learning Models Task-1
9	Build Deep Learning Models Task-1
10	Build Deep Learning Models Task-2
11	Build Deep Learning Models Task-2
12	Build Late Fusion Pipeline
13	Model optimizations and Hyper-parameter tuning
14	Evaluation and Result analysis
15	Document final report and presentation

References:

1. Ferda Ofli, Firoj Alam, and Muhammad Imran, **Analysis of Social Media Data using Multimodal Deep Learning for Disaster Response,** In Proceedings of the 17th International Conference on Information Systems for Crisis Response and Management (ISCRAM), 2020, USA.
2. Firoj Alam, Ferda Ofli, and Muhammad Imran, **CrisisMMD: Multimodal Twitter Datasets from Natural Disasters,** In Proceedings of the 12th International AAAI Conference on Web and Social Media (ICWSM), 2018, Stanford, California, USA.