CIS 5300 Final Project Milestone 1

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1 Related Work

In the paper [3], the authors employ a novel approach to the CrisisMMD dataset, combining CNNs for both text and image data from social media to enhance disaster response. They introduce a joint representation learning approach using two parallel deep learning architectures. For images, they use the VGG16 network architecture, extracting high-level features from images, and for text, they define a CNN with five hidden layers. These feature vectors from both modalities are then integrated into a shared representation, followed by a dense layer and a softmax prediction layer, a process known as early fusion. The team conducted experiments using three training settings: one using both text and image data, one using only text, and one using only images. The experimental results show that their multimodal approach significantly outperforms the models trained on a single modality (text or image alone). The best model in the multimodal setting achieved an F1-score of 84.2 for the informativeness classification task and 78.3 for the humanitarian classification task.

The paper [1] presents Image4Act, an end-to-end pipeline for filtering and classifying Twitter images to support disaster response operations. It combines human computation and machine learning to handle noisy, high-volume social media data. Relevance filtering and deduplication are done using deep neural networks and perceptual hashing, achieving AUC/accuracy scores of 0.98. Additional custom classifiers for damage assessment are created via crowdsourcing. Evaluations show the damage classifier reaches an AUC of 0.72. Real-world deployment during a cyclone filtered images with 0.67-0.92 precision. Overall, Image4Act enables extracting actionable insights from social media imagery to aid humanitarian organizations.

The paper [4] introduces a labelled data-efficient strategy to identify COVID-19 informative tweets with a limited number of labelled instances, achieving an F1-score of 91.23. The approach applies data augmentation to expand the training set, enhancing the performance of pre-trained language models with just 14.3% of the full dataset size. The authors address the challenges of attaining comparable performance with fewer data, the effectiveness of various augmentation methods, and the reasons for improved model efficiency through augmentation. Leveraging transformer-based models like CT-BERT, RoBERTa, and BERTweet, along with augmentation techniques such as AEDA, EDA, BT, and T5-based paraphrasing, the study shows that CT-BERT fine-tuned with on tweets nearly matches the performance achieved with 7000 tweets. This finding underscores the potential of their data-efficient method for situations where large-scale labelling is impractical.

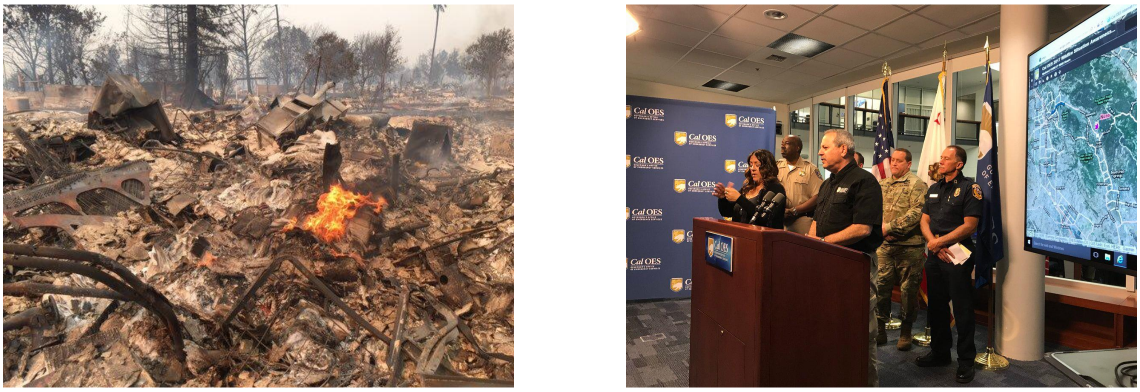
2 Data

We are using version 2.0 of the `CrisisMMD: Multimodal Crisis Dataset` introduced by the authors in [2]. The 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 authors who created the dataset also introduced 3 associated learning tasks. We are working on Task 1, which is a binary classification task to determine whether a given tweet or image is useful for humanitarian aid purposes ("Informative") or not ("Not informative").

Our data consists of TSV files for the train/dev/test splits and an images folder, and we are using the train/dev/test splits provided by the dataset creators. The complete data can be found `here` (in the Gradescope submission, we have not included the image files due to size constraints). Each TSV file contains the following columns:

1. `event_name`: Disaster event name eg. "california_wildfires"
2. `tweet_id`: Tweet ID eg. 917791291823591425
3. `image_id`: Combination of tweet_id and an index concatenated with an underscore, where the integer indices represent different images associated with a given tweet eg. "917791291823591425_0"
4. `tweet_text`: Tweet text eg. "RT @Cal_OES: PLS SHARE: Weâ€™re capturing wildfire response, recovery info here: https://t.co/r89LKpjLPj https://t.co/HiA1oQF2Ax"
5. `image`: Relative path of an image inside the "data_image" folder for a given tweet eg. "data_image/california_wildfires/10_10_2017/917791291823591425_0.jpg"
6. `label`: Randomly selected label from label_text and label_image
7. `label_text`: "informative" if the text is informative and "not_informative" otherwise
8. `label_image`: "informative" if the image is informative and "not_informative" otherwise
9. `label_text_image`: "Positive" if label_text and label_image are the same and "Negative" otherwise

For our text-only strong baseline we plan to use `label_text` as the label, and for all other models we plan to use `label` as the label. The train, dev, and test sets consist of 13608, 2237, and 2237 samples respectively. The % of "informative" samples for `label_text` for the train, dev, and test sets are 70.826, 72.061, and 72.061 respectively. Likewise, the % of "informative" samples for `label` for the train, dev, and test sets are 61.295, 62.897, and 61.377 respectively.



(a) Informative image

(b) Not informative image

Figure 1: Examples of informative and not informative images

References

[1] Firoj Alam, Muhammad Imran, and Ferda Ofli. "Image4Act: Online Social Media Image Processing for Disaster Response". In: *2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*. Sydney, NSW, Australia: IEEE/ACM, 2017, pp. 601–604.

[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)*. USA, June 2018.

[3] Ferda Ofli, Firoj Alam, and Muhammad Imran. "Analysis of Social Media Data using Multimodal Deep Learning for Disaster Response". In: *17th International Conference on Information Systems for Crisis Response and Management*. ISCRAM. ISCRAM, May 2020.

[4] A. Santhanavijayan Srinivasulu Kothuru. "Identifying COVID-19 english informative tweets using limited labelled data". In: *Social Network Analysis and Mining*. 2023.