

CS5803: Natural Language Processing

Project Title: Disaster Tweet Classification

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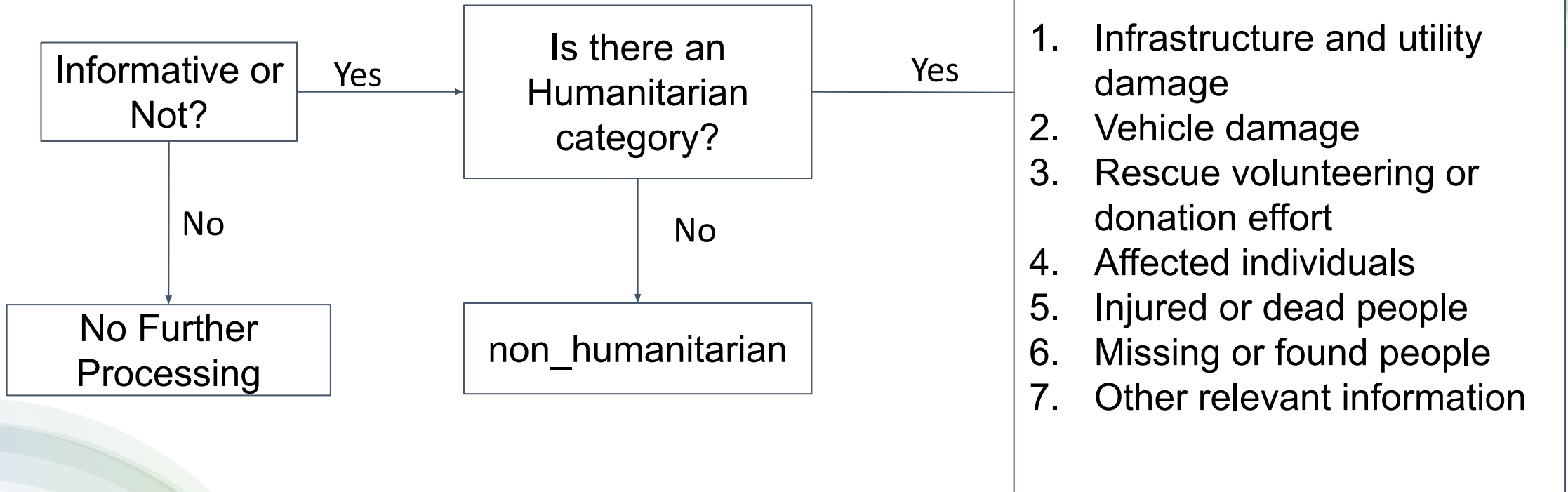
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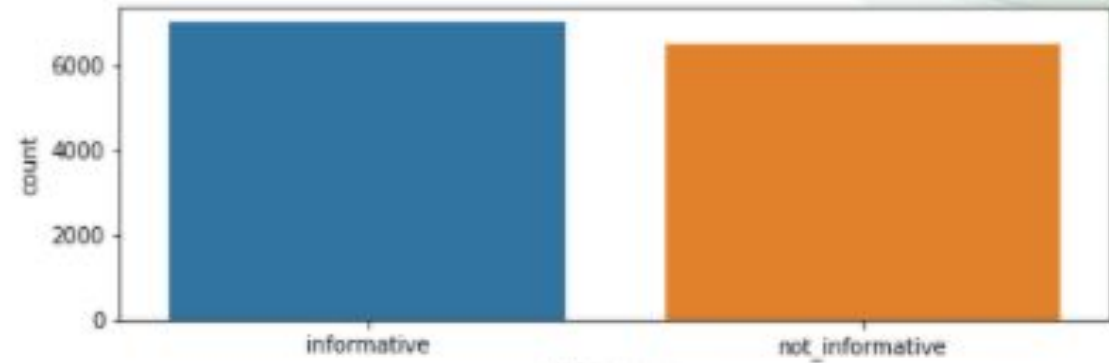
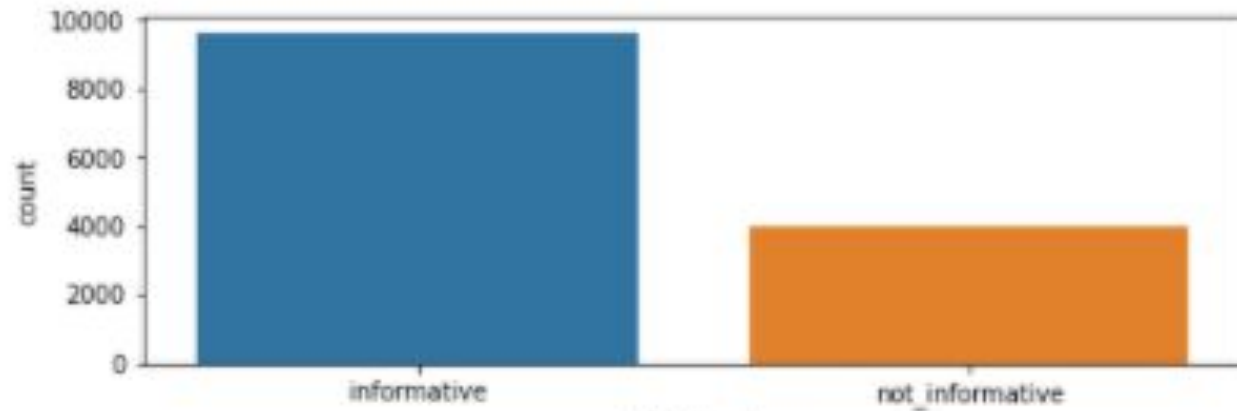
Problem Statement

- During a disaster, people share huge information on Social Media which can be used to respond to the calamity.
- Proper and timely information can help the disaster response teams immensely.
- This project aims to classify tweets in informative and non-informative tweets to extract important information.
- The overall task involves three subtasks finding if a tweet contains information related to disaster, whether any humanitarian aid is required and how much damage has been caused.
- The task needs to be performed sequentially as a pipeline (if a task is informative then only it is processed further to see if humanitarian need is required).

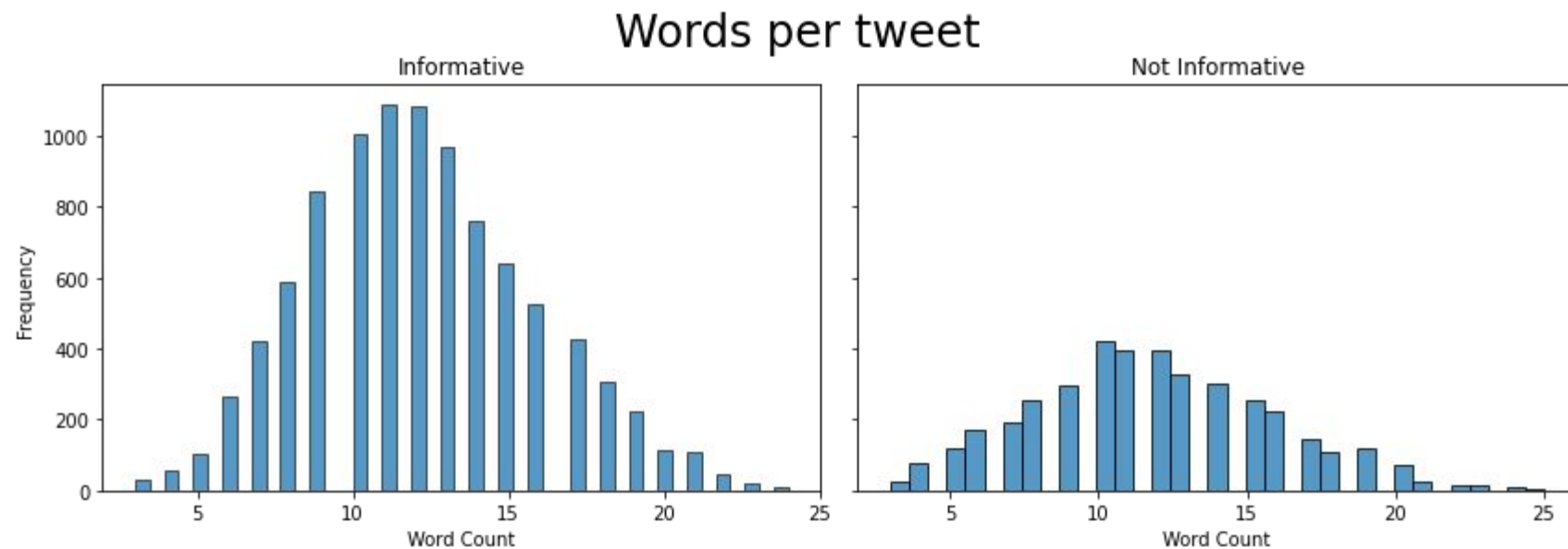
Problem Statement



Dataset Details: CrisisMMD



Dataset Details: CrisisMMD



Largest tweets in train, dev and test set

42

37

37

Dataset Details: CrisisMMD



Informative
Other relevant information



Informative
Affected individuals



Informative
Infrastructure and utility
damage
Severe damage



Not informative
Not humanitarian



Informative
Infrastructure and utility
damage
Severe damage



Informative
Infrastructure and utility
damage
Severe damage



Informative
Infrastructure and utility
damage
Severe damage



Informative
Infrastructure and utility
damage
Severe damage

0 (480, 640, 3) 1

Sample #0



1 (900, 1200, 3) 0

Sample #1



2 (346, 512, 3) 1

Sample #2



3 (352, 512, 3) 1

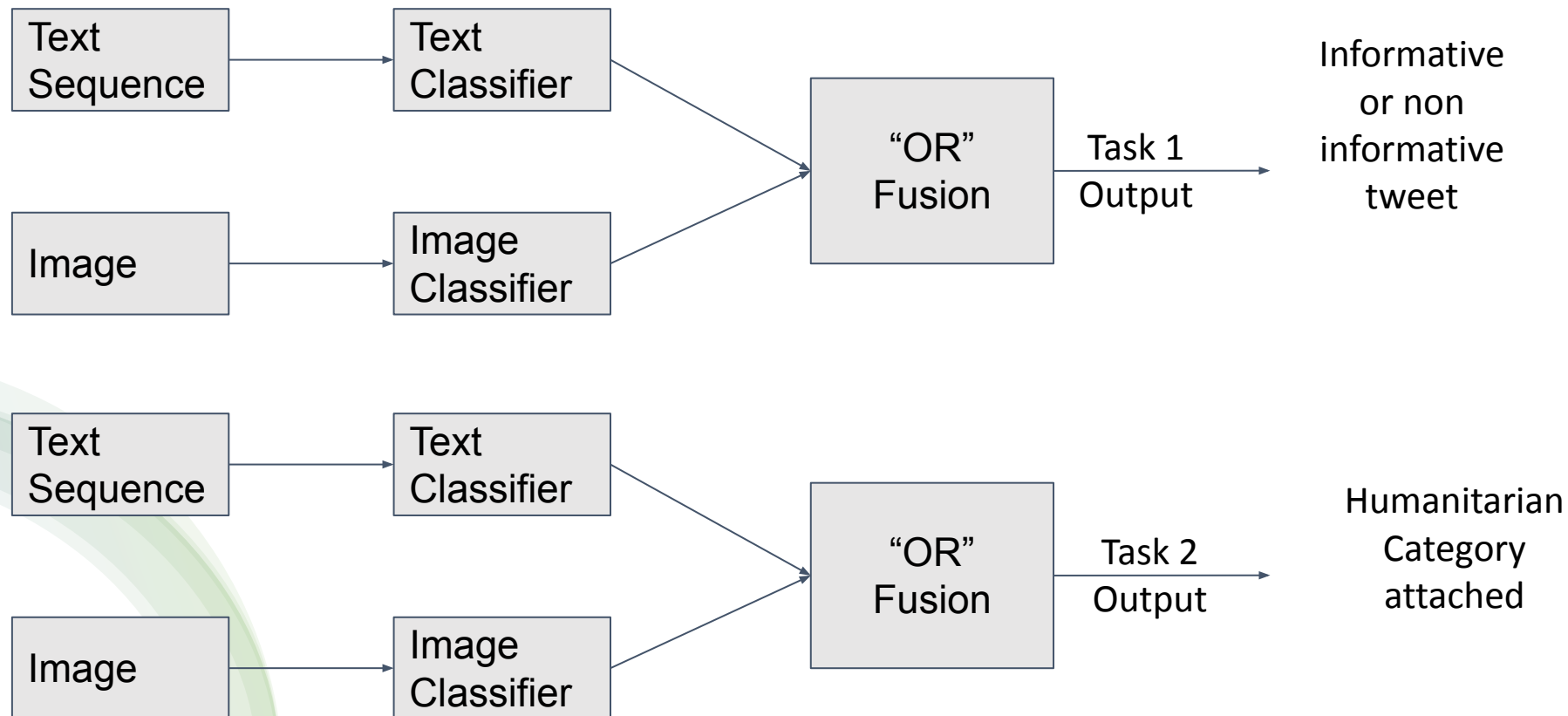
Sample #3



Source: <https://aidr-dev2.qcri.org/apps/crisismmd>

Proposed Solution

- The problem is a multimodal (sequence and image) classification task.
- The labels of texts and images of the tweets are not always same and so the predictions from the two might also be different.



We divide problem in four smaller parts.

Task 1:

- Part 1: -Text classification (Informative vs Non Informative)
- Part 2: -Image Classification (Informative vs Non Informative)

Task 2:

- Part 1: -Text classification (Humanitarian Categories)
- Part 2: - Image Classification (Humanitarian Categories)

Task 1, Part 1: - Text Classifier

- Tweets are cleaned and tokenized.
- Integer encoding is done for labels (0 and 1)
- Weight sampler is used during text classification segment for Task-1 to deal with Class imbalance.
- Transformer (Bert Pre-Trained Classifier) model is used.
- Binary Cross entropy loss is used to get logits.
- Train the model and save model.

```
RT CalOES PLS SHARE Were capturing wildfire response recovery info here  
['rt', 'cal', '##oes', 'pl', '##s', 'share', 'were', 'capturing', 'wild', '##fire', 'response', 'recovery', 'info', 'here']  
[19387, 10250, 22504, 20228, 2015, 3745, 2020, 11847, 3748, 10273, 3433, 7233, 18558, 2182]
```

Results for Task 1, Part 1: -

Loss kept on decreasing for Validation set. Also we were able to achieve good accuracy for Non informative and informative task.

```
Average training loss: 0.2980
Accuracy: 0.7997
F1 Score: 0.8732
Average training loss: 0.2340
Accuracy: 0.8082
F1 Score: 0.8781
Average training loss: 0.1928
Accuracy: 0.8149
F1 Score: 0.8820
Average training loss: 0.1925
Accuracy: 0.8131
F1 Score: 0.8807
Average training loss: 0.1872
Accuracy: 0.8127
F1 Score: 0.8805
```

Task 1, Part 2: - Image Classifier

- Images are varied size so rescaled to 256x256, and then random cropped to 224x224.
- Integer encoding is done for labels (0 and 1)
- Model pre-trained on imagenet with ResNet-18 as backbone is used.
- The final FC layers are trained for few epochs
- Binary Cross entropy loss is used to get logits.

Results for Task 1, Part 2: -

Loss kept on decreasing for Validation set. Also we were able to achieve good accuracy for Non informative and informative task.

```
Training....  
Accuracy: 0.7808  
Train Loss: 0.0072  
-----  
Validating....  
Accuracy: 0.7992  
loss: 0.4340  
epoch number : 4  
Training....  
Accuracy: 0.7825  
Train Loss: 0.0071  
-----  
Validating....  
Accuracy: 0.8037  
loss: 0.4243  
epoch number : 5  
Training....  
Accuracy: 0.7893  
Train Loss: 0.0069  
-----  
Validating....  
Accuracy: 0.8176  
loss: 0.4211
```

Task 2, Part 1: - Text Classifier

- Tweets are cleaned and tokenized.
- Integer encoding is done for labels (0, 1,2,3,4,5,6,7,8)
- Transformer (Bert Pre-Trained Classifier) model is used.
- Cross entropy loss is used to get logits.
- Train the model and save model.

Results for Task 2, Part 1: -

Loss kept on decreasing for Validation set. Also we were able to achieve good accuracy for Non informative and informative task.

```
Average training loss: 0.2980
Accuracy: 0.7997
F1 Score: 0.8732
Average training loss: 0.2340
Accuracy: 0.8082
F1 Score: 0.8781
Average training loss: 0.1928
Accuracy: 0.8149
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Average training loss: 0.1925
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Average training loss: 0.1872
Accuracy: 0.8127
F1 Score: 0.8805
```

Task 2, Part 2: - Image Classifier

- Images are varied size so rescaled to 256x256, and then random cropped to 224x224.
- Integer encoding is done for labels (0, 1,2,3,4,5,6,7,8)
- Model pre-trained on imagenet with ResNet-18 as backbone is used.
- The final FC layers are trained for few epochs
- Cross entropy loss is used.
- We saved the model for this task

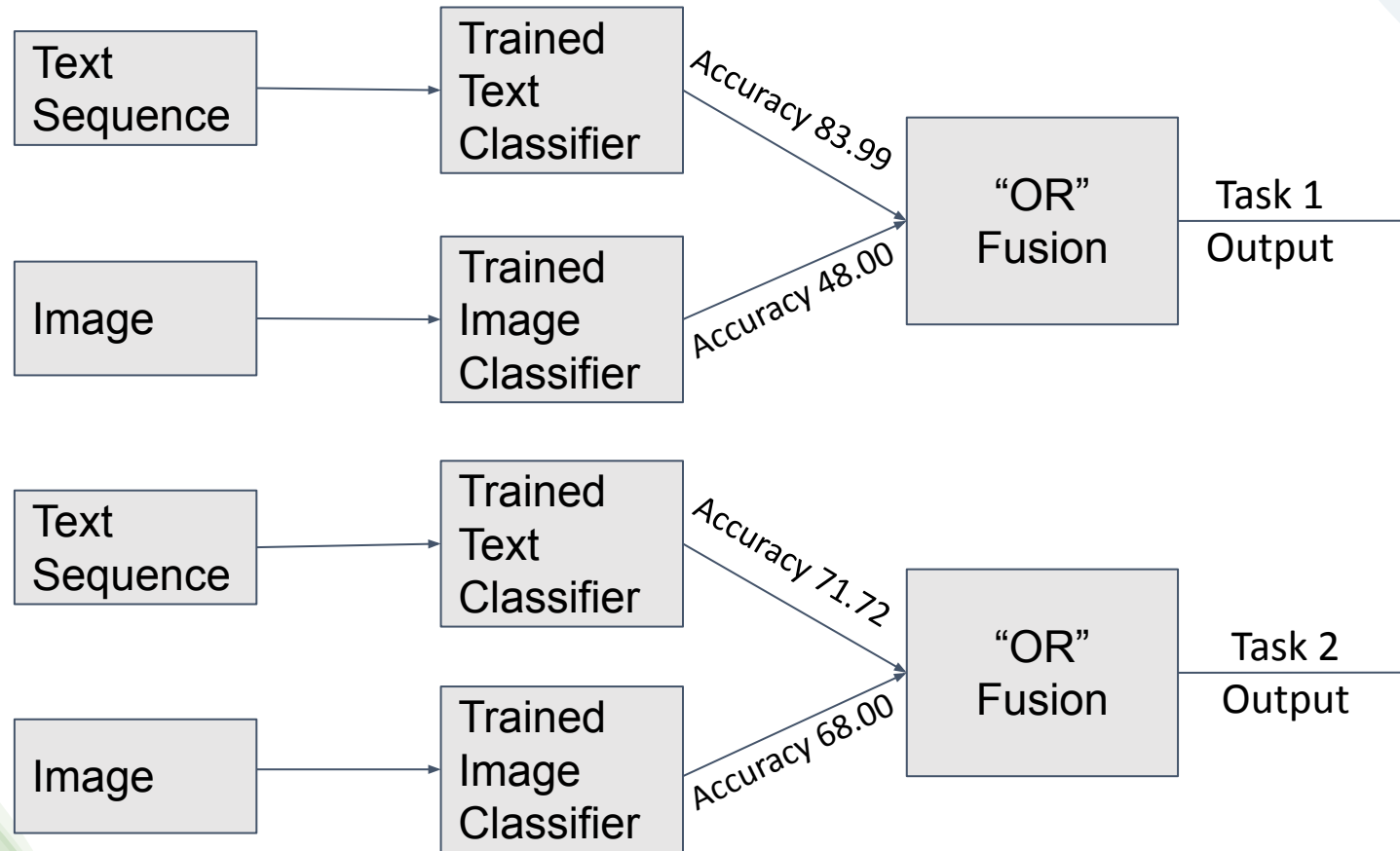
Results for Task 2, Part 2: -

Loss kept on decreasing for Validation set. Also we were able to achieve good accuracy for Non informative and informative task.

Train Epoch: 3	[0/13608 (0%)]	Loss: 0.875640
Train Epoch: 3	[1280/13608 (9%)]	Loss: 0.645636
Train Epoch: 3	[2560/13608 (19%)]	Loss: 1.189980
Train Epoch: 3	[3840/13608 (28%)]	Loss: 1.187590
Train Epoch: 3	[5120/13608 (38%)]	Loss: 0.788357
Train Epoch: 3	[6400/13608 (47%)]	Loss: 0.922565
Train Epoch: 3	[7680/13608 (56%)]	Loss: 1.054267
Train Epoch: 3	[8960/13608 (66%)]	Loss: 0.857649
Train Epoch: 3	[10240/13608 (75%)]	Loss: 0.643040
Train Epoch: 3	[11520/13608 (85%)]	Loss: 1.037572
Train Epoch: 3	[12800/13608 (94%)]	Loss: 0.806707

Test set: Average loss: 0.9467, Accuracy: 1524/2237 (68%)

Inference :-



Conclusion

- To be able to gather information from tweets around the world during the disaster time can be helpful.
- Information Can be used to provide medical aid, infrastructure, relief packages etc.
- MultiModal nature of problem is sometimes hard to manage as varied information flows in from different sources.

References

- 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
- Xukun Li, Doina Caragea, Improving Disaster-related Tweet Classification with a Multimodal Approach, Social Media for Disaster Response and Resilience Proceedings of the 17th ISCRAM Conference, 2020
- Hua XS., Zhang HJ., An Attention-Based Decision Fusion Scheme for Multimedia Information Retrieval. In: Aizawa K., Nakamura Y., Satoh S. (eds) Advances in Multimedia Information Processing - PCM 2004.

The image features a white background with decorative curved lines in the corners. In the top-right corner, there is a thick, multi-layered arc that transitions from a light blue color to a light green color. In the bottom-left corner, there is a similar thick, multi-layered arc that also transitions from a light blue color to a light green color. The text "Thank you." is centered in the middle of the page.

Thank you.