Evaluating the Performance of Deep Learning Methods for Hurricane-Related Image Classification

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INTRODUCTION

Global social media use during natural disasters has been well documented (Murthy et al., 2017). In the U.S., public social media platforms are often a primary venue for those affected by disasters. Some disaster victims believe first responders will see their public posts and that the 9-1-1 telephone system becomes overloaded during crises. Moreover, some feel that the accuracy and utility of information on social media is likely higher than traditional media sources. However, sifting through content during a disaster is often difficult due to the high volume of 'non-relevant' content. In addition, text is studied more than images posted on Twitter, leaving a potential gap in understanding disaster experiences. Images posted on social media during disasters have a high level of complexity (Murthy et al., 2016). Our study responds to O'Neal et al.'s (2017) call-to-action that social media images posted during disasters should be studied using machine learning.

METHODOLOGY

Our study develops/evaluates a transfer learning framework for classifying 17,843 images posted to Twitter. We use VGG-16, a Convolutional Neural Network (CNN) to categorize images shared on Twitter during Hurricane Harvey in 2017 by their urgency, relevance, time period, and the presence of damage and relief motifs.

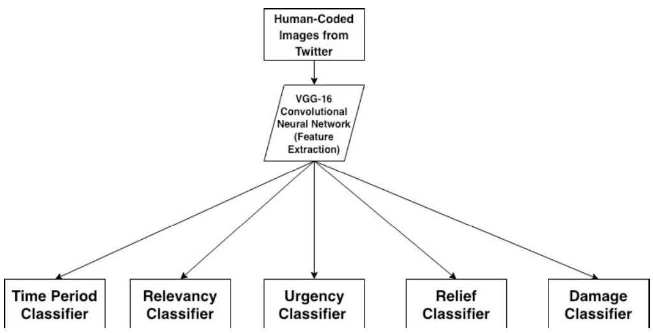

Figure 1: Deep Learning Framework

Human Annotation: To develop the 'training' dataset (i.e., data used to train an algorithm) for our study, we randomly sampled 1,128 images (approximately 6.45% of all images collected) and human-coded these images using a rubric with categories drawn from established crisis literature.

Deep 'Transfer' Learning for Feature Extraction: Because most deep learning techniques require large datasets and computational resources, it is common to employ a pre-trained model and adapt it to a specific learning task. In this study, we treat output from the second-to-last layer of VGG-16 as low-dimensional 'feature vectors' representing each image. Using these feature vectors, we trained five multilayer perceptrons to classify images by time period, relevancy, urgency and the presence of 'damage' and 'relief' themes. We used nearly identical model architectures for the classifiers, and we evaluate each classifier's accuracy, categorical cross-entropy loss, and F1(-macro/-micro) scores.

RESULTS

Existing crisis-related image filtering approaches using deep learning indicate state of the art baselines with F1 scores ranging from 0.60-0.70 (Nguyen et al., 2017). Our results, particularly with the relevancy, urgency, and damage classifiers (see Table 1), provide evidence that we can obtain high-performance, robust classifiers even with just 1,128 human-annotated images.

Classifier	Time Period	Urgency	Relevancy	Damage	Relief
Training Loss	0.6398	0.9514	0.3313	0.1441	0.128
Training Accuracy	0.7705	0.6098	0.9035	0.9957	0.9484
Validation Loss	0.7515	1.0841	0.5222	0.253	0.2335
Validation Accuracy	0.677	0.6195	0.8186	0.9023	0.9336
F1 Macro Score	0.3735	0.5847	0.752	0.6973	0.824
F1 Micro	0.5012	0.6157	0.811	0.4375	0.7568

Table 1: Classifier Results for Accuracy, Loss, and F1

CONCLUSIONS AND FURTHER WORK

Our framework reliably classifies images based on relevancy, urgency, and damage. Stakeholders such as emergency response organizations do not have to create custom models. Our transfer learning models can be used real-time to filter images by urgency, relevancy, and damage. During future hurricane events, this will not only save time, but help target limited resources to look at relevant images posted on social media

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